

# 人工智能算法在芯片缺陷检测中的应用

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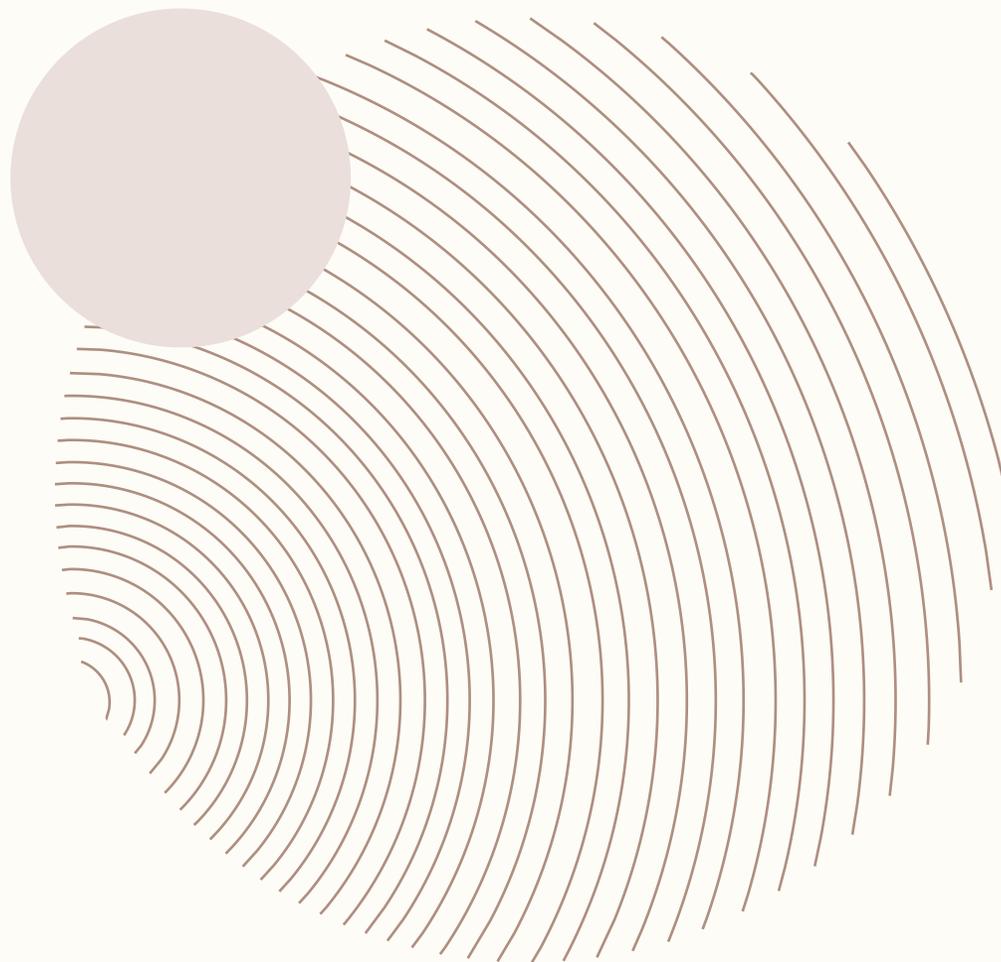
武汉大学

2025.07.16 西安

# 目录

- 人工智能与高能物理
- 工业缺陷检测现状
- 无监督缺陷检测方法
- 光纤端面/光芯片缺陷检测

# 人工智能与高能物理



# 如何评估/计算不同数据分布的差异?

Sliced Wasserstein Distance介绍

# Kullback–Lieibler divergence (KL散度)

## KL散度使用时存在的问题

- KL散度缺乏直观“可解释性”；
- KL散度缺乏对称性；

$$D_{KL}(P\|Q) \neq D_{KL}(Q\|P)$$

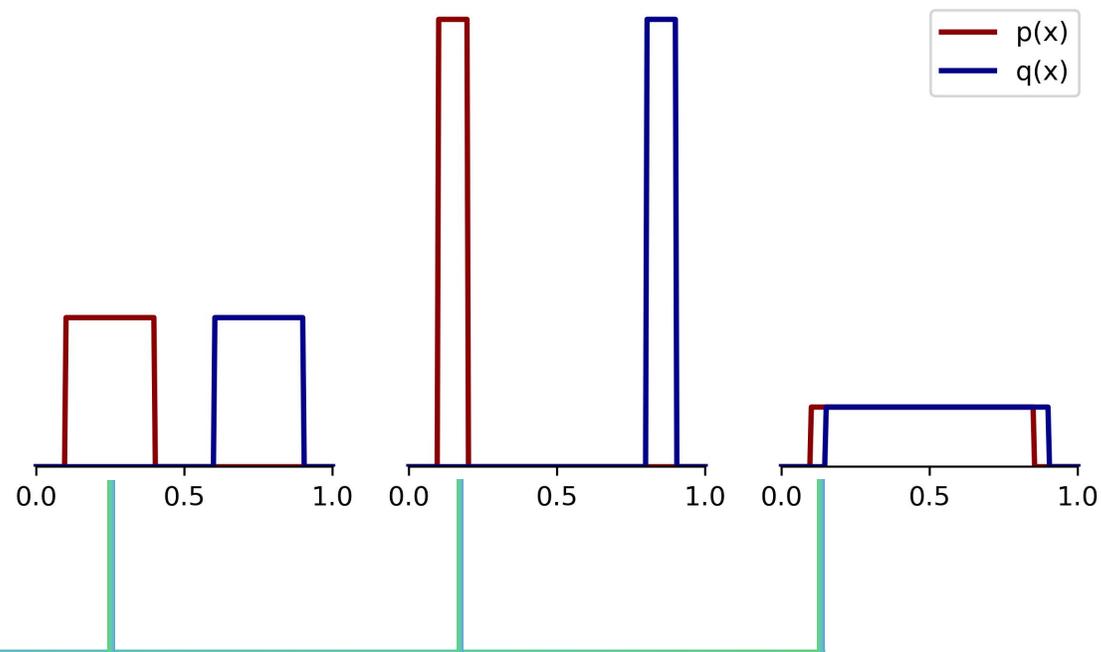
- KL散度存在发散问题。

$$D_{KL}(P\|Q) = D_{KL}(Q\|P) = +\infty$$

$q(x) = 0$  但  $p(x) > 0$

## KL散度的定义

$$D_{KL}(P\|Q) = \int p(x) \log\left(\frac{p(x)}{q(x)}\right) dx$$



<https://alexwilliams.info/itsneuronalblog/2020/10/09/optimal-transport/>

# Wasserstein Distance (WD)

## Wasserstein Distance 的定义

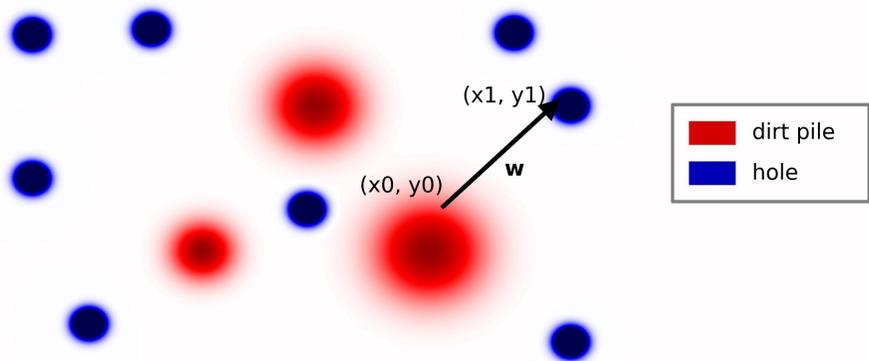
$$\text{total cost} = \int \int \int \int C(x_0, y_0, x_1, y_1) \cdot T(x_0, y_0, x_1, y_1) dx_0 dy_0 dx_1 dy_1$$

$$C(x_0, y_0, x_1, y_1) = (x_0 - x_1)^2 + (y_0 - y_1)^2$$

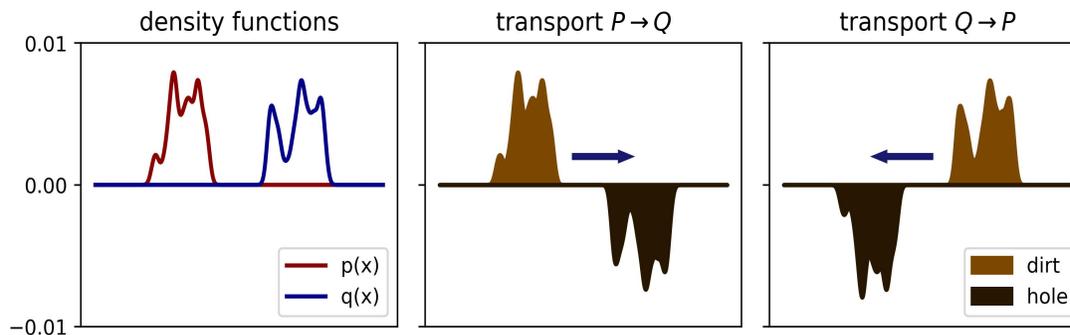
$$T(x_0, y_0, x_1, y_1) = w$$

$$\int \int T(x_0, y_0, x, y) dx dy = p(x_0, y_0) \quad \text{for all starting locations } (x_0, y_0).$$

$$\int \int T(x, y, x_1, y_1) dx dy = q(x_1, y_1) \quad \text{for all destinations } (x_1, y_1).$$



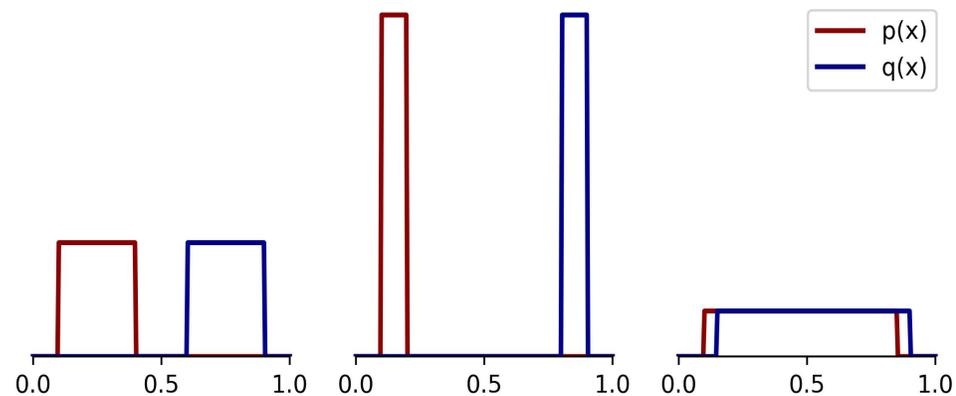
<https://alexhwilliams.info/itsneuronalblog/2020/10/09/optimal-transport/>



$$\mathcal{W}(P, Q) = 0.503$$

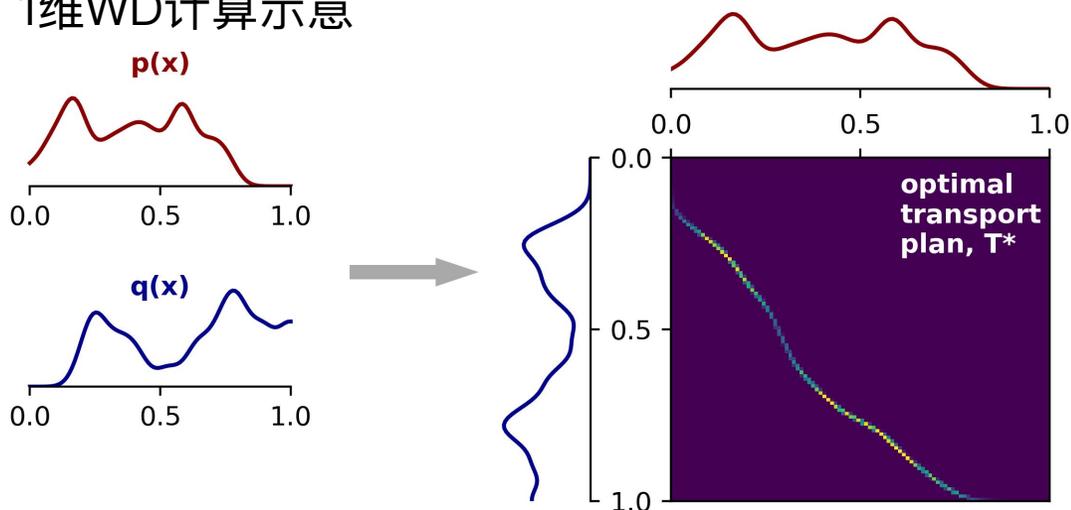
$$\mathcal{W}(P, Q) = 0.704$$

$$\mathcal{W}(P, Q) = 0.05$$

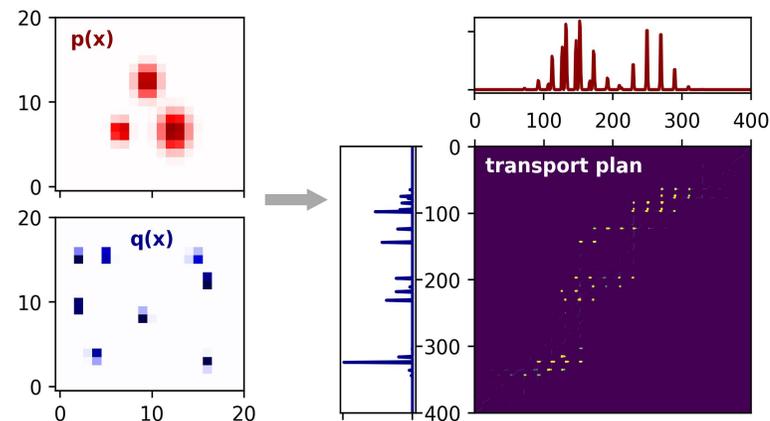


# Wasserstein Distance的计算

1维WD计算示意



2维WD计算示意



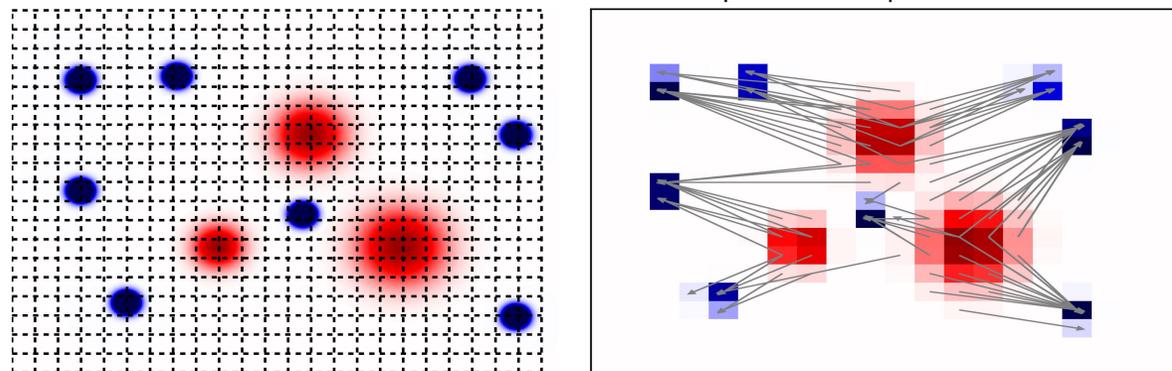
## 1维离散数据的WD计算非常直接

$$\alpha = \frac{1}{n} \sum_{i=1}^n \delta_{x_i} \quad \beta = \frac{1}{n} \sum_{i=1}^n \delta_{y_i}$$

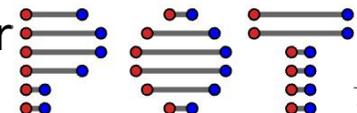
其中  $x_1 \leq \dots \leq x_n$  和  $y_1 \leq \dots \leq y_n$

$$W_p(\alpha, \beta)^p = \frac{1}{n} \sum_{i=1}^n |x_i - y_i|^p$$

Optimal Transport Solution!



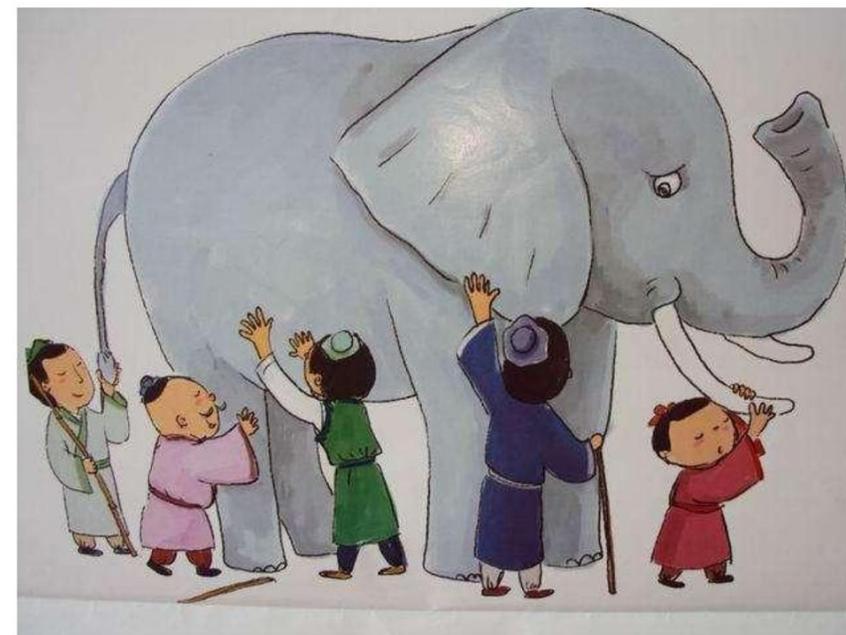
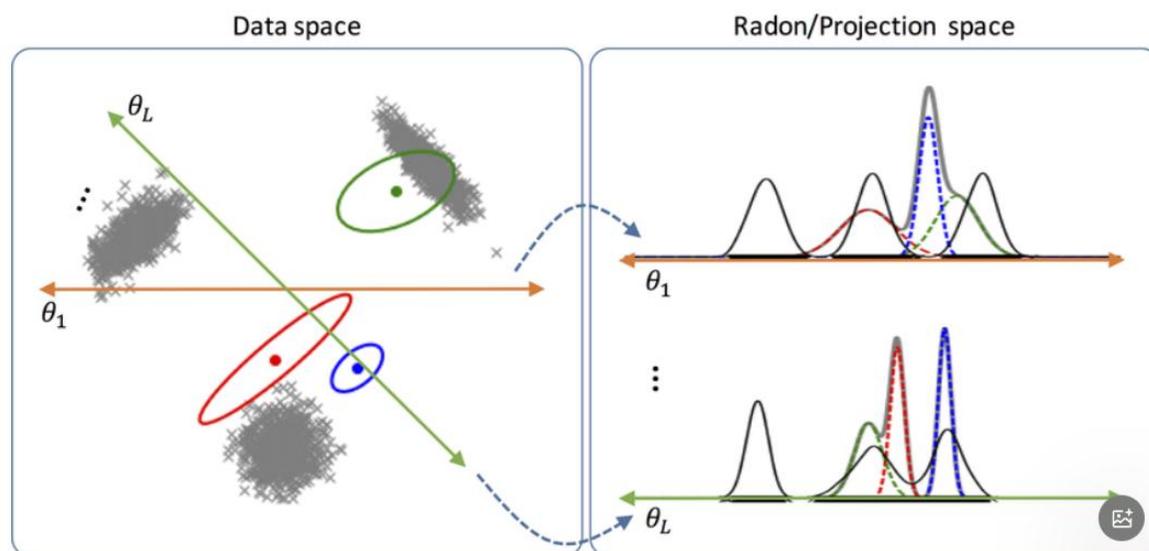
POT Python Optimal Transport  
<https://pythonot.github.io/>



# Sliced Wasserstein Distance (SWD)

## SWD计算原理

- **投影**: 将高维的概率分布投影到多个随机投影方向 $\theta_L$ 上;
- **计算1维WD**: 对于每个投影方向计算1维分布的WD;
- **平均或积分**: 将所有投影方向上的1维WD进行综合。



## SWD的优点:

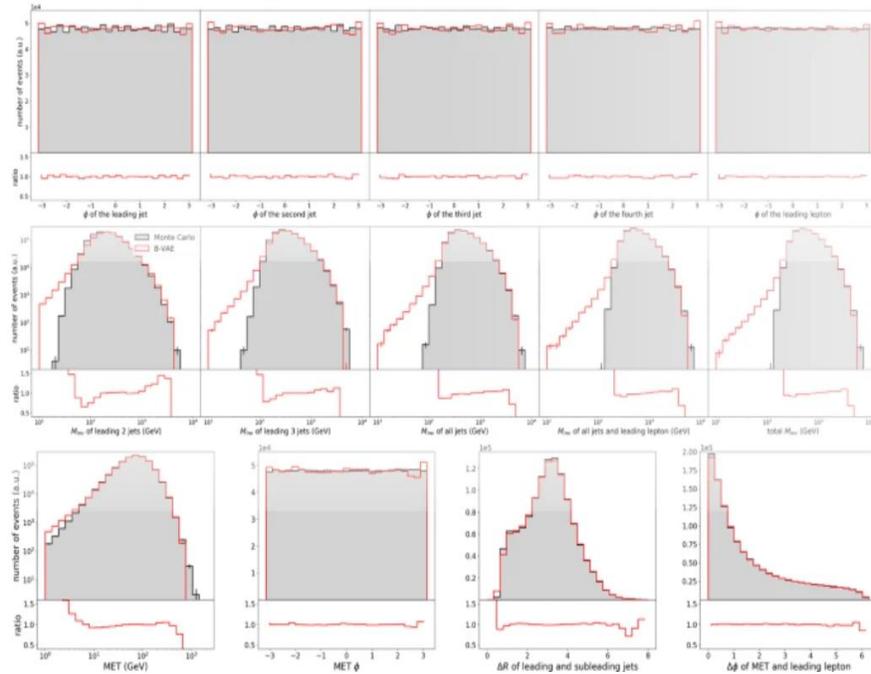
- **计算效率高**: 能有效处理大规模数据和高维数据;
- **保留分布特征**: 可有效用于同分布检验;
- **理论性质好**: 满足度量的基本性质。

# SWD作为损失函数用于高能物理的优势

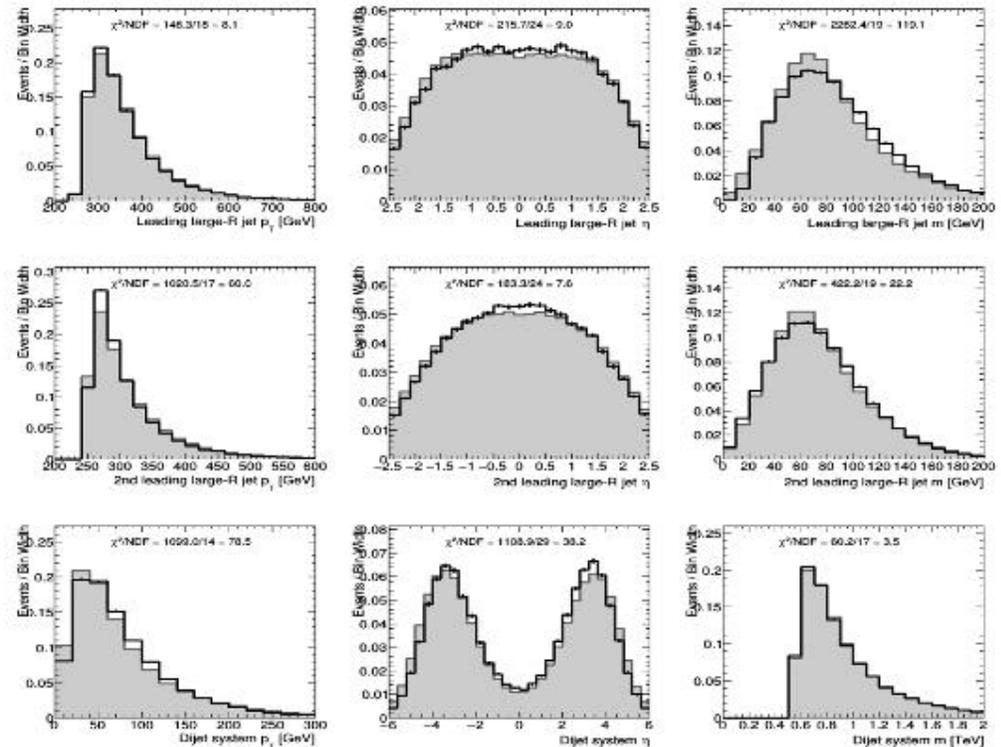
	不依赖模型	高维特性	结合AI能力
$\chi^2$	√	×	×
Likelihood	×	√	×
SWD	√	√	√

# 应用1: SWD Generation (学习并产生特定分布)

## 已有的利用神经网络学习特定分布的最佳结果



Distributions for the ground truth (gray) and samples generated by the B-VAE with  $\dim z = 20$ ,  $B = 10^{-6}$ ,  $\alpha = 1$  and  $\gamma = 0.05$  (red).

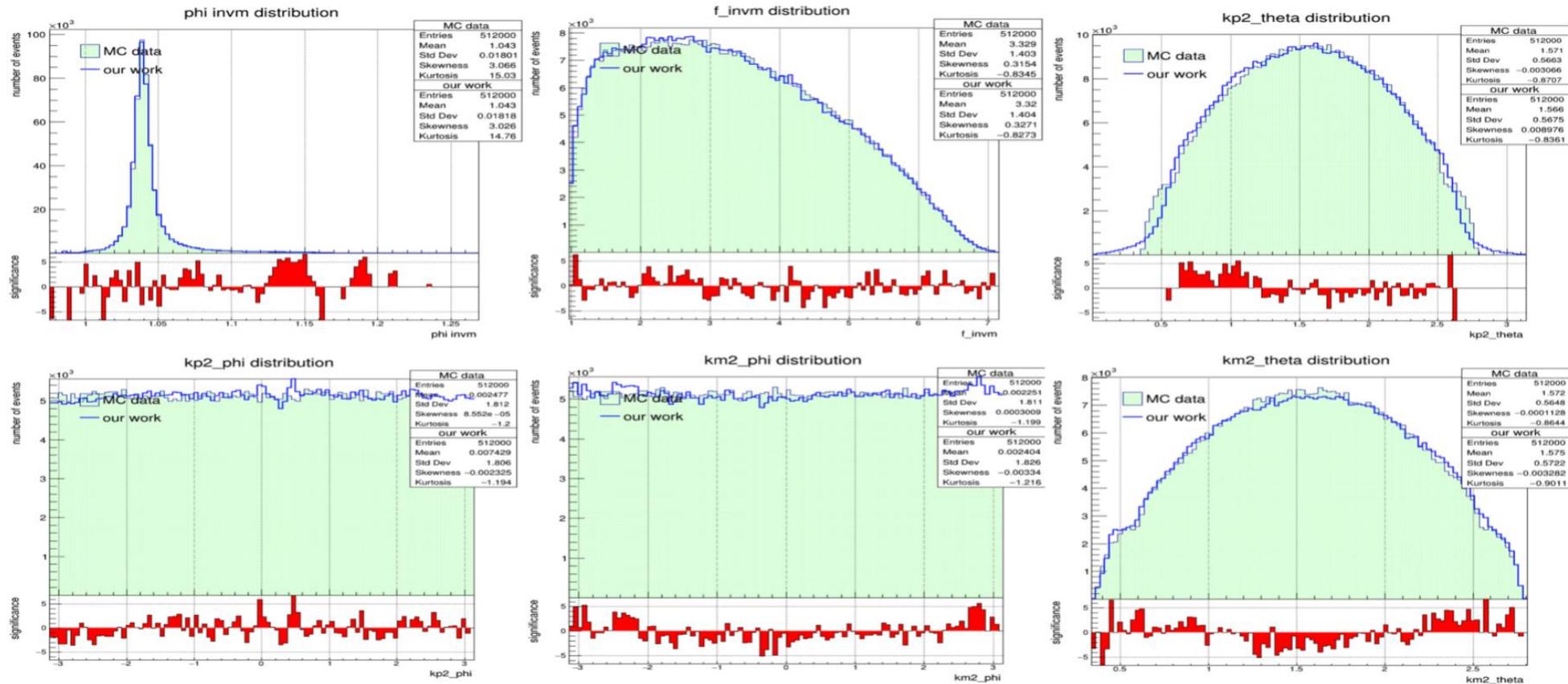


Otten, S., Caron, S., de Swart, W. et al. Event generation and statistical sampling for physics with deep generative models and a density information buffer. **Nat Commun 12, 2985 (2021)**

Di Sipio, Riccardo, et al. "DiJetGAN: a generative-adversarial network approach for the simulation of QCD dijet events at the LHC." **JHEP 2019.8 (2019)**

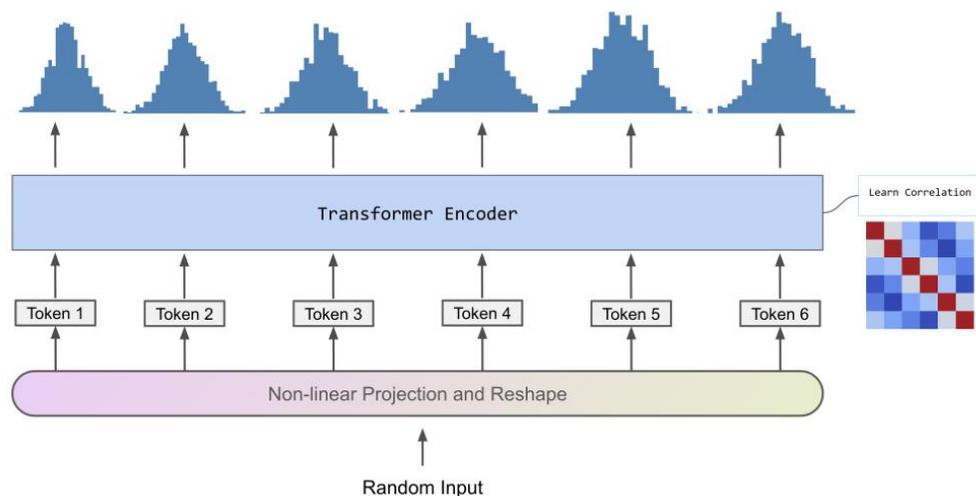
# 应用1: SWD Generation (学习并产生特定分布)

通过对于GAN添加额外约束得到了看起来更好的结果, 但无法描述数据分布不同维度的关联性。



# 应用1: SWD Generation (学习并产生特定分布)

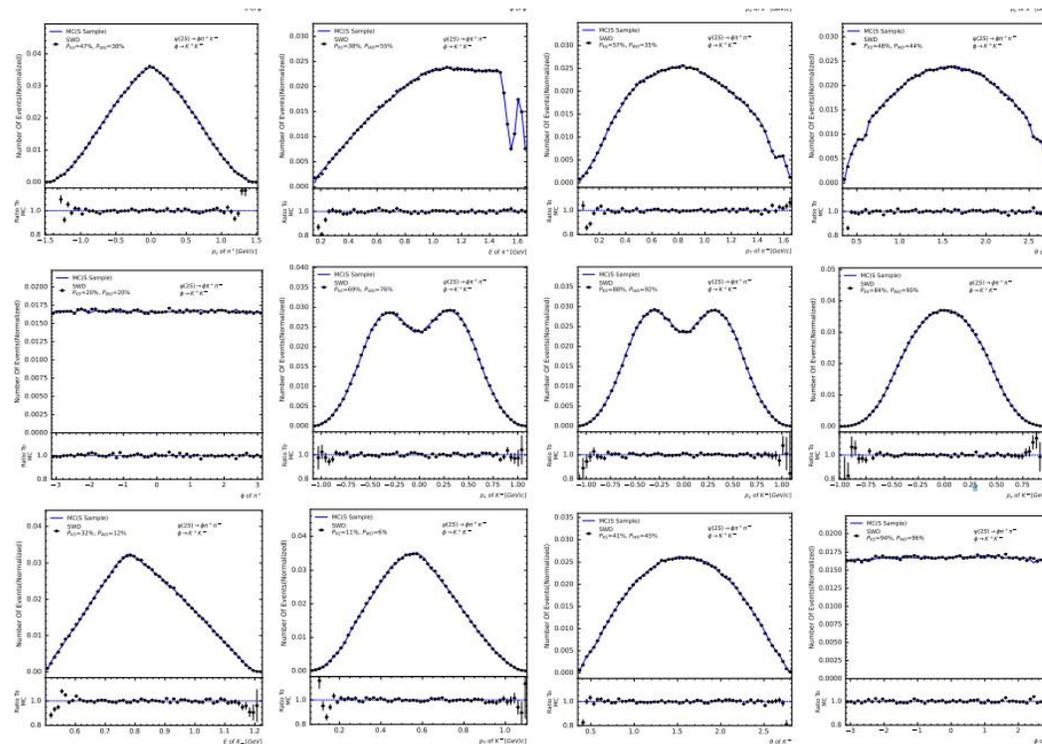
SWD与生成式神经网络的结合得到了目前最好的事例产生器



**Fig. 6: Model Overview** We input the random samples from uniform distribution, non-linearly expand it, split into desired tokens and feed it into a standard Transformer encoder to learn correlation of multi-variable distribution. Finally we can generate the reasonable high dimensional data

SWD与生成式神经网络的结合诞生了迄今为止最佳的快模拟结果，在高维空间中达到了以假乱真的效果。

<https://github.com/caihao/SWD-EvtGen>



**Fig. 1: 1D Histograms of the specific projection distributions** Distributions of samples generated by standard config

<https://arxiv.org/abs/2310.17897>  
97  
(潘楚钺, 董翔, 蔡浩等)

## 应用2: SWD Permutation Test (同分布检验)



道高一尺, 还是魔高一丈?

最强Particle Gun



最强  
同分布检验工具

# 应用2：SWD Permutation Test (同分布检验)

## Permutation Test (置换检验)

也被称为随机化检验或重排检验，是基于数据重排的非参数统计检验方法

- **假设前提**：置换检验基于零假设，即样本数据之间不存在特定的差异或关系，所有观测值都是可交换的，它们的不同排列组合都是等可能的。
- **数据重排**：在零假设成立的前提下，对观测数据进行重新排列或置换，得到大量的新数据集。例如，在比较两个样本组 A 和 B 时，将两组数据合并后再随机分配到两个新的组中，模拟零假设下的数据情况。
- **计算统计量**：对于每个重排后的数据集，计算与原假设相关的统计量，如均值差异、方差比、相关系数等。
- **构建分布**：通过多次重排和计算统计量，得到统计量的经验分布。这个分布反映了在零假设成立时，统计量可能出现的取值范围和概率分布。
- **确定 p 值**：将原始数据计算得到的统计量与重排得到的统计量分布进行比较，计算出在重排分布中，出现与原始统计量同样极端或更极端值的概率，即 p 值。如果 p 值小于预先设定的显著性水平（如 0.05），则拒绝零假设，认为观测到的数据差异或关系不是由随机因素导致的，而是具有统计学意义。



**Sliced  
Wasserstein  
Distance**

# 应用2: SWD Permutation Test (同分布检验)

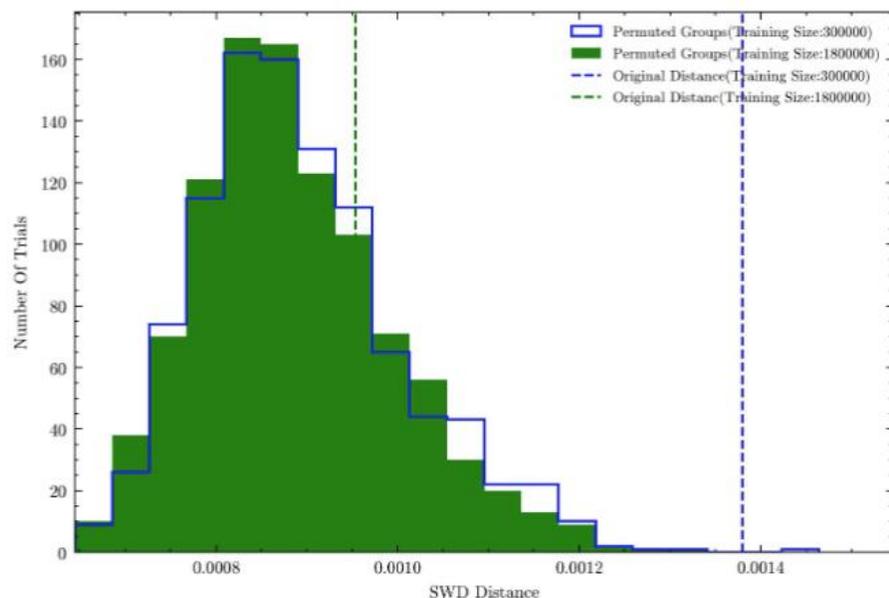


FIG. 4: **Permutation Test** We illustrates the SWD distance distributions obtained via the permutation test for two distinct training sample sizes (300,000 vs. 1.8 million events). Each bar corresponds to the frequency of SWD distances generated through random permutations of the data. The vertical dashed lines mark the observed SWD distances from the unpermuted datasets

<https://arxiv.org/abs/2310.17897>  
(潘楚钺, 董翔, 蔡浩等)

TABLE III: **Test Sample Size vs. Permutation-Test p-Value** This table reports p-values for a model trained on 300,000 events under varying test sample sizes. For smaller test sets (i.e., below 350,000 events), the p-value remains above the 5% threshold, indicating no statistically significant difference between the generated and target distributions.

Test Sample ( $\times 10^4$ )	P Value (%)
5	60.1%
10	33.3%
15	36.0%
20	7.7%
25	11.6%
30	5.9%
<b>35</b>	<b>5.1%</b>
40	2.5%
45	4.7%
50	3.2%

TABLE II: **Effect of Training Sample Size on Model Performance** This table reports the Sliced Wasserstein Distance (SWD) between the generated and target distributions using 1 million test events, along with the corresponding permutation-test p-value, for varying training sample sizes. As the training set increases, the SWD tends to decrease and the p-value generally rises, indicating reduced evidence of distributional discrepancy. Once the training sample surpasses roughly 750,000 events, the p-value exceeds 5%, suggesting that the model's learned distribution is no longer statistically distinguishable from the target distribution at conventional significance levels.

Training Sample ( $\times 10^5$ )	SWD test distance ( $\times 10^3$ )	SWD test p value
18.0	0.9551	26.6%
15.0	0.8893	45.3%
12.5	1.0309	11.1%
10.0	0.9356	27.9%
<b>7.5</b>	<b>1.0538</b>	<b>7.4%</b>
5.0	1.2293	0.7%
2.5	1.5182	0%
1.0	1.5774	0%
0.5	2.3670	0%

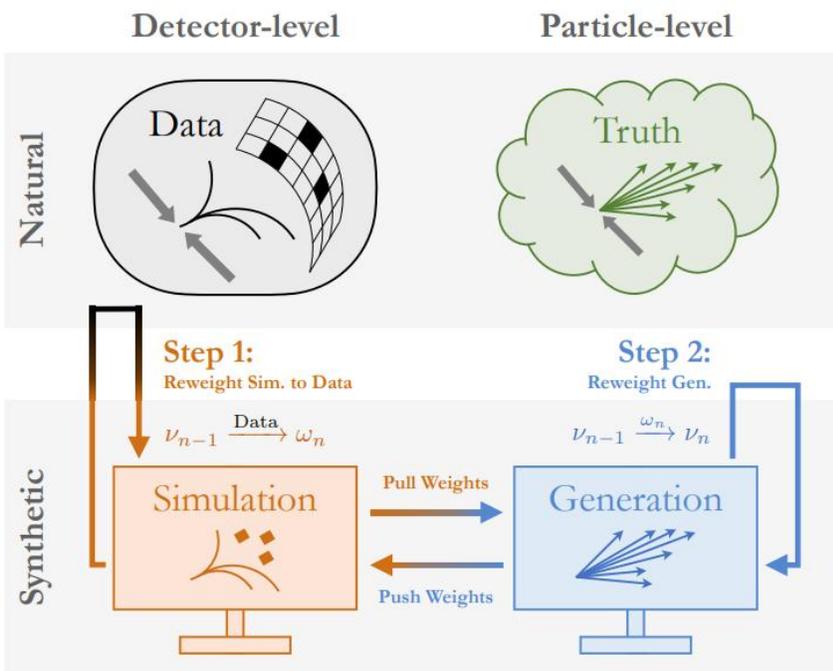
现有的同分布检验方法并不能有效辨别SWD产生数据与目标数据，我们将SWD与Permutation Test结合实现了：

**“最强的矛 vs. 最强的盾”**

也就是说SWD产生的数据只有基于SWD的同分布检验方法才能分辨。

# 应用3：SWD Unfolding（修正探测器效应）

已有的利用神经网络学习特定分布的最佳结果



Phys. Rev. Lett. 124, 182001 (2020)

2020年，Anders Andreassen等人基于似然比开发了OmniFold，得到当时最佳的unfolding结果，并进行了实际应用。

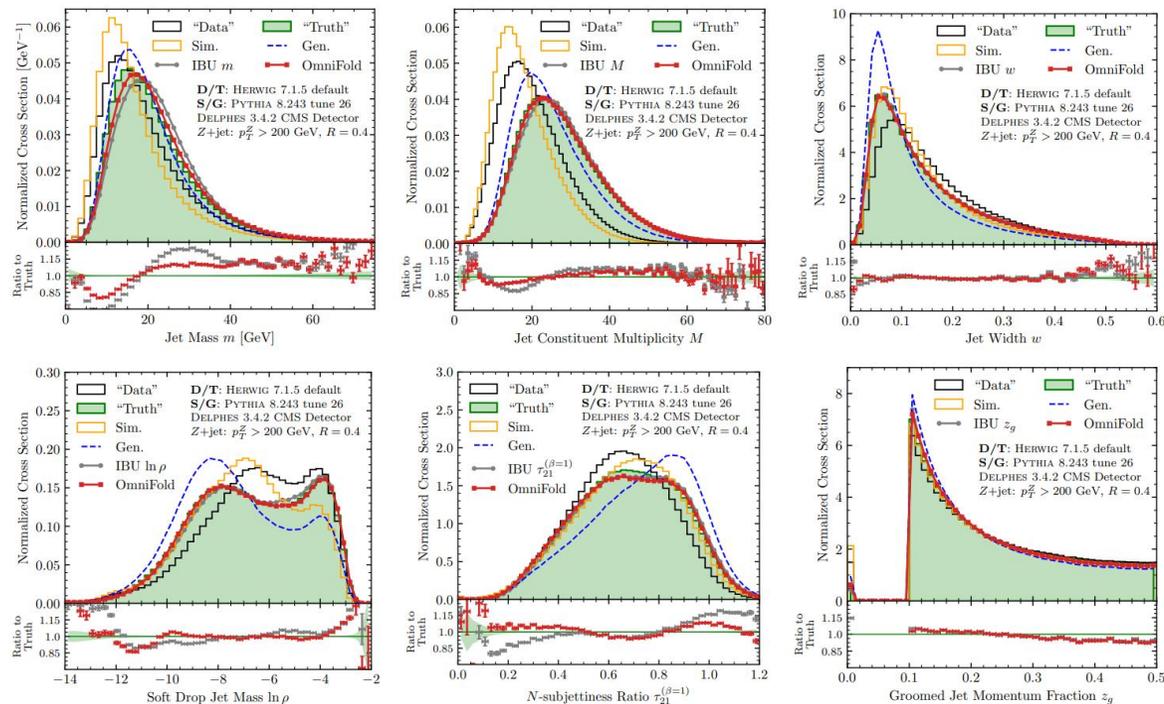


FIG. 2. The unfolding results for six jet substructure observables, using HERWIG 7.1.5 (“Data”/“Truth”) and PYTHIA 8.243 tune 26 (Sim./Gen.), unfolded with OMNIFOLD and compared to IBU. OMNIFOLD matches or exceeds the unfolding performance of IBU on all of these observables. We emphasize that OMNIFOLD is a single general unfolding procedure, whereas unfolding with IBU must be done observable by observable. Statistical uncertainties are shown only in the ratio panel.

# 应用3：SWD Unfolding（修正探测器效应）

我们开发的SWDFold取得了目前最好的Unfolding效果，  
并实际用于分波分析（待投稿）

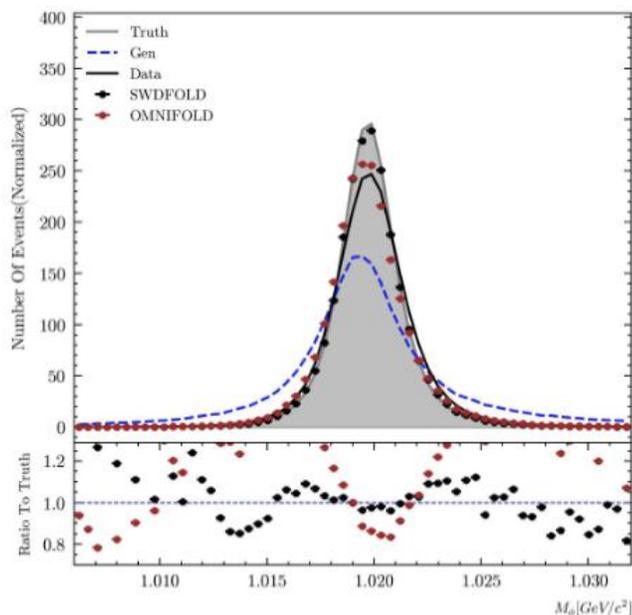


Figure 2: Histogram Analysis of Unfolding Methodologies. The performance of our proposed SWDFOLD method is shown with brown dots, compared with the OMNIFOLD method with black dots. Our SWDFOLD method exhibits a high degree of congruence with the truth event (Truth), signifying a successful reweighting of the generation event distribution (Gen) to estimate the truth event distribution (Truth), as particularly evident in the sharp peak around  $1.020 \text{ GeV}/c^2$  in the plot.

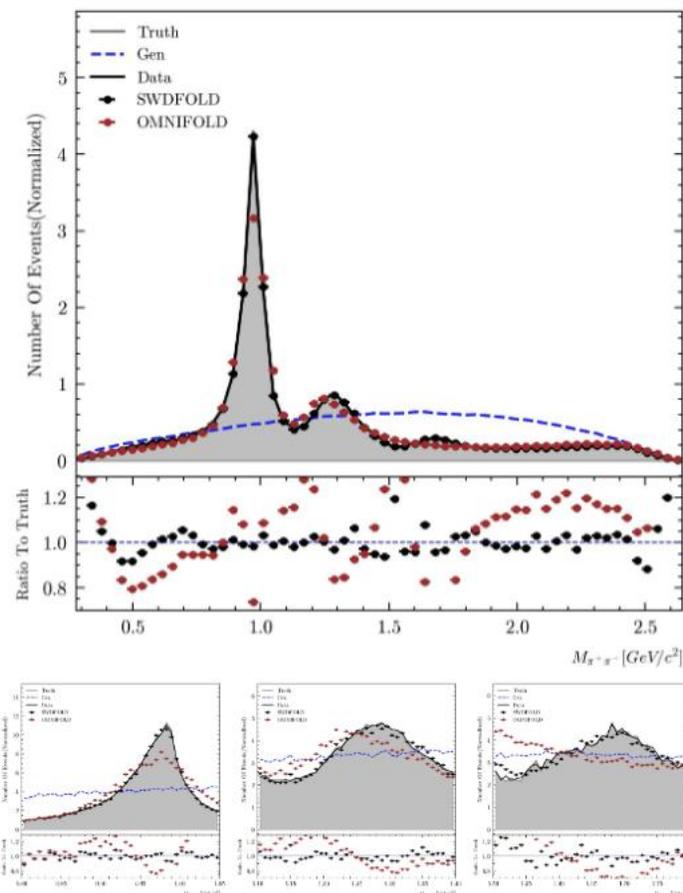
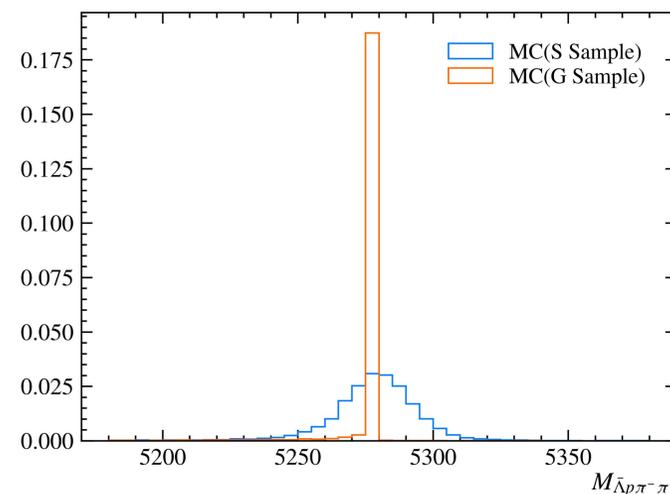
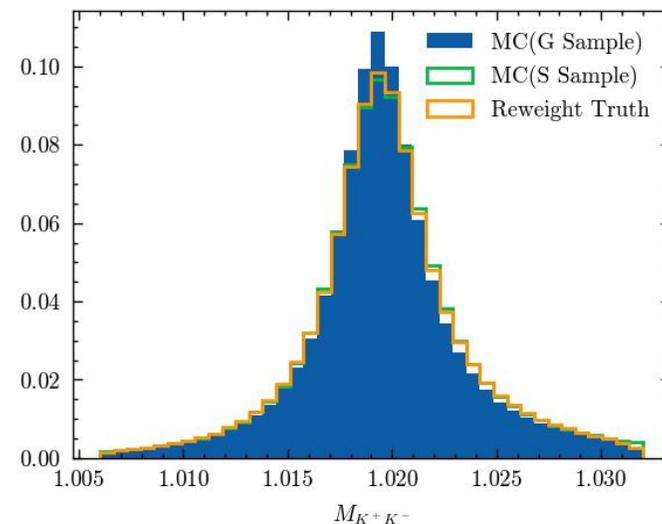
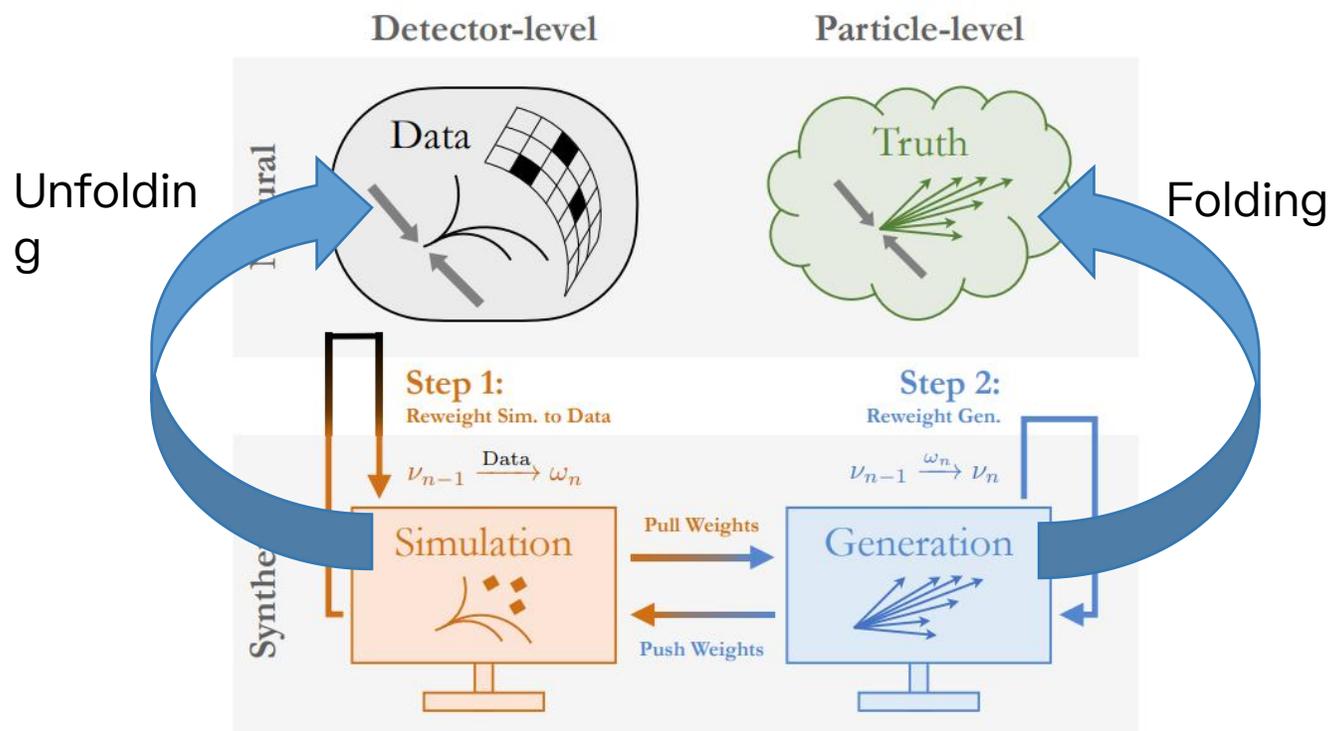


Figure 3: Histogram Analysis of Reweight Methodologies. We present a detailed examination of the  $\pi^+\pi^-$  mass distribution across three distinct mass ranges:  $(0.8, 1.05)$ ,  $(1.1, 1.4)$ , and  $(1.5, 1.8) \text{ GeV}/c^2$ . The performance of the SWDFOLD method, illustrated by the black line, showcases its ability to reveal the resonance peaks by reweighting the Generation Event (Gen), aligning closely with the Truth Event (Truth) in both peak value and width.

# 应用4: SWD Reweight / SWD Folding

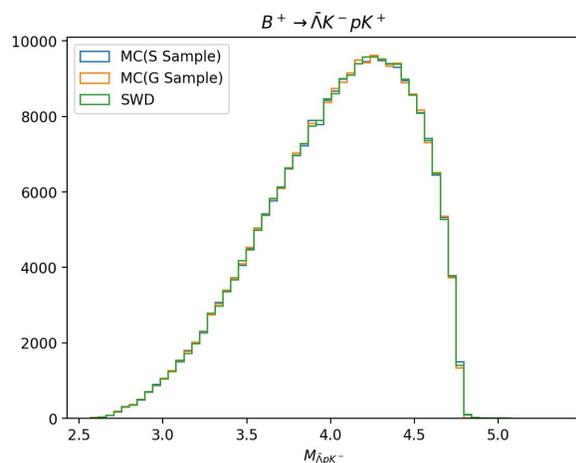


- SWD Reweight是目前最强的unbinned reweight方法;
- SWD Folding/SWD Unfolding在高能物理模拟中有广泛应用;
- 基于模拟数据的SWD Folding在Generation相空间覆盖不足时存在局限性。

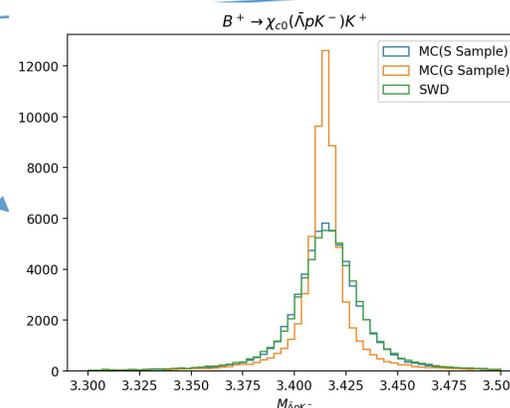
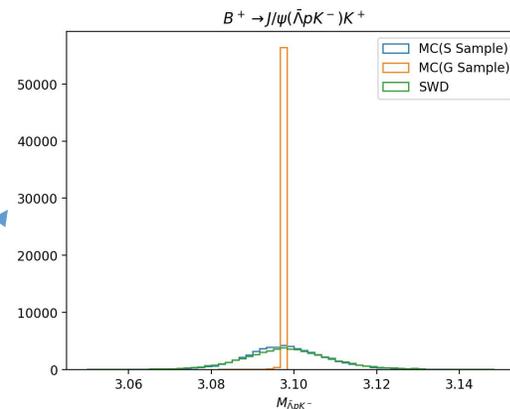
# 应用5：SWD Simulation（高精度快速模拟）

对于同末态的衰变过程，其探测器效应可以认为是类似的，只是动力学分布不相同。

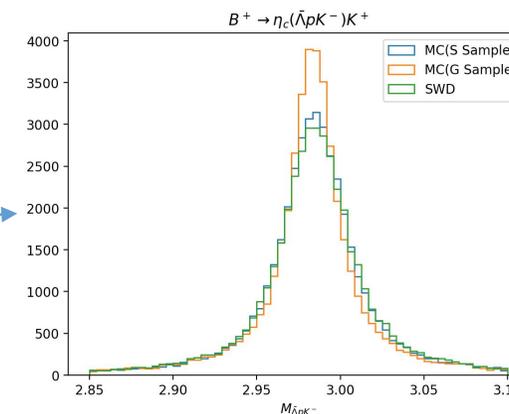
我们尝试使用 $B^+ \rightarrow \bar{\Lambda} p K^- K^+$ 的四体衰变样本进行训练MC（Generation Sample）到MC（Simulation Sample）的过程，学习到探测器效应，再直接迁移到同末态，但不同物理过程的MC（Generation Sample）中，使其能模拟出对应的MC（Simulation Sample）的形状



训练样本 ( $B^+ \rightarrow \bar{\Lambda} p K^- K^+$ )

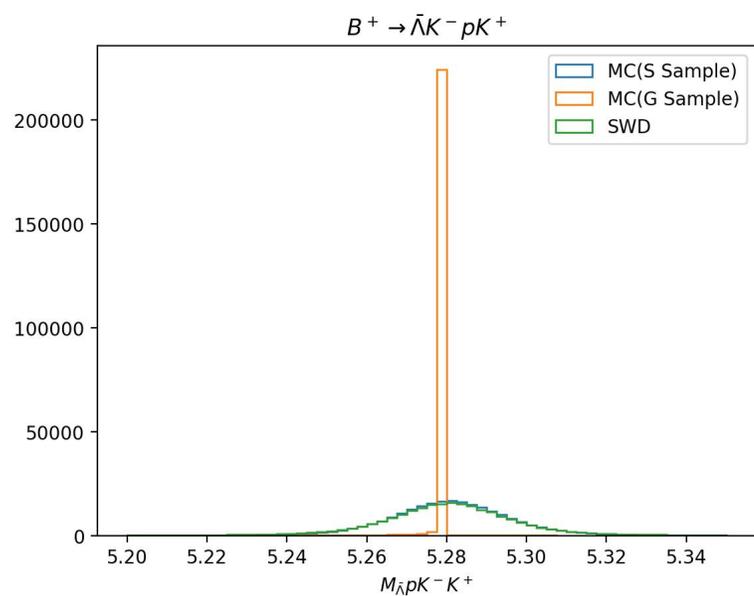


测试样本 ( $J/\psi, \eta_c, \chi_{c0}$ )

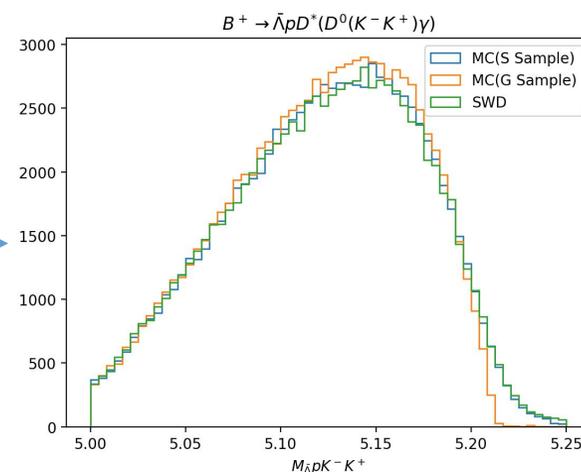
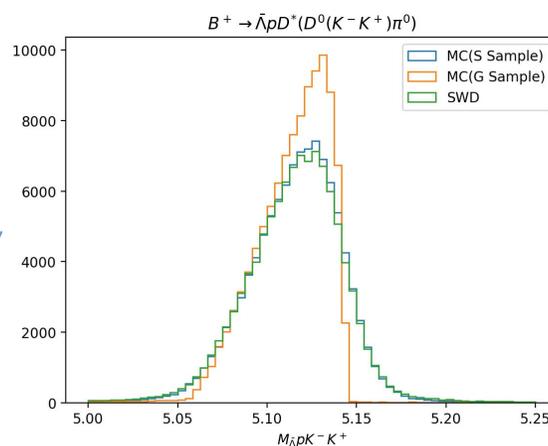


# 应用5：SWD Simulation（高精度快速模拟）

对于部分重建本底，物理分析中通常只关心形状，可以用该方法从其MC（Generation Sample）中快速模拟出经过探测器后的形状，实现与传统快模拟更高效，甚至更高精度的快模拟方法



训练样本 ( $B^+ \rightarrow \bar{\Lambda} p K^- K^+$ )



测试样本 ( $D^* \rightarrow D^0 \pi^0, D^* \rightarrow D^0 \gamma$ )

## 应用5：SWD Simulation（高精度快速模拟）

基于迁移学习的快模拟充分说明探测对于事例的响应是可以学习到的。

$$B^+ \rightarrow J/\psi(\bar{\Lambda}pK^-)K^+ \quad (\text{部分重建本底测试})$$

$$B^+ \rightarrow \eta_c(\bar{\Lambda}pK^-)K^+ \quad B^0 \rightarrow \bar{\Lambda}pD^-(K^+K^-\pi^-)$$

$$B^+ \rightarrow \bar{\Lambda}p\bar{D}_0(K^-K^+) \quad B^0 \rightarrow \bar{\Lambda}pD^{*-}(K^+K^-\pi^-)$$

$$B^+ \rightarrow \chi_{c0}(\bar{\Lambda}pK^-)K^+ \quad B^+ \rightarrow \bar{\Lambda}pD^{*0}(D^0(K^+K^-\pi^0))$$

$$B^+ \rightarrow \bar{\Lambda}p\phi(K^-K^+) \quad B^+ \rightarrow \bar{\Lambda}pD^{*0}(D^0(K^+K^-\gamma))$$

$$B^+ \rightarrow \chi_{c1}(\bar{\Lambda}pK^-)K^+$$

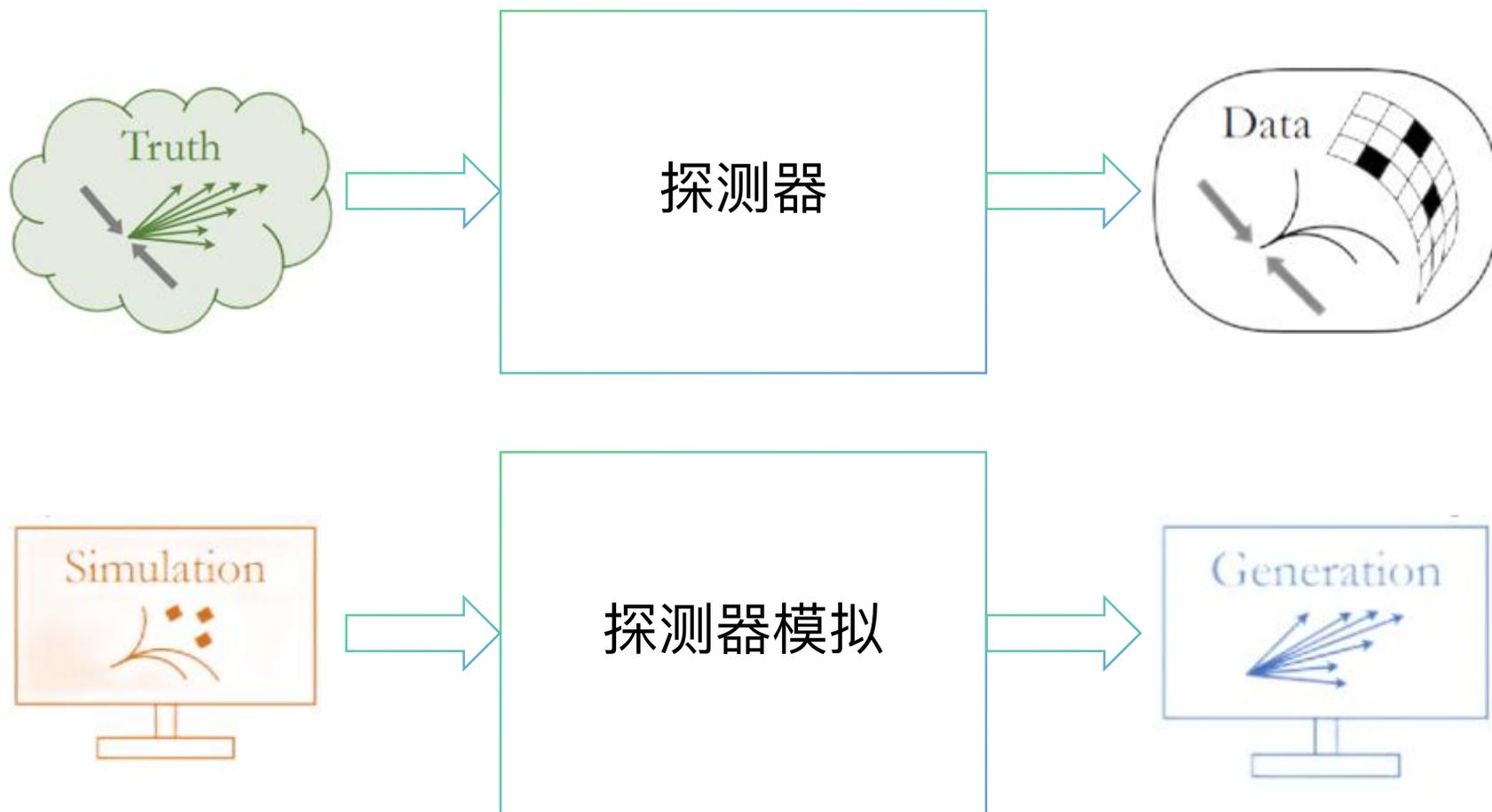
$$B^+ \rightarrow \chi_{c2}(\bar{\Lambda}pK^-)K^+$$

$$B^+ \rightarrow \psi(2S)(\bar{\Lambda}pK^-)K^+$$

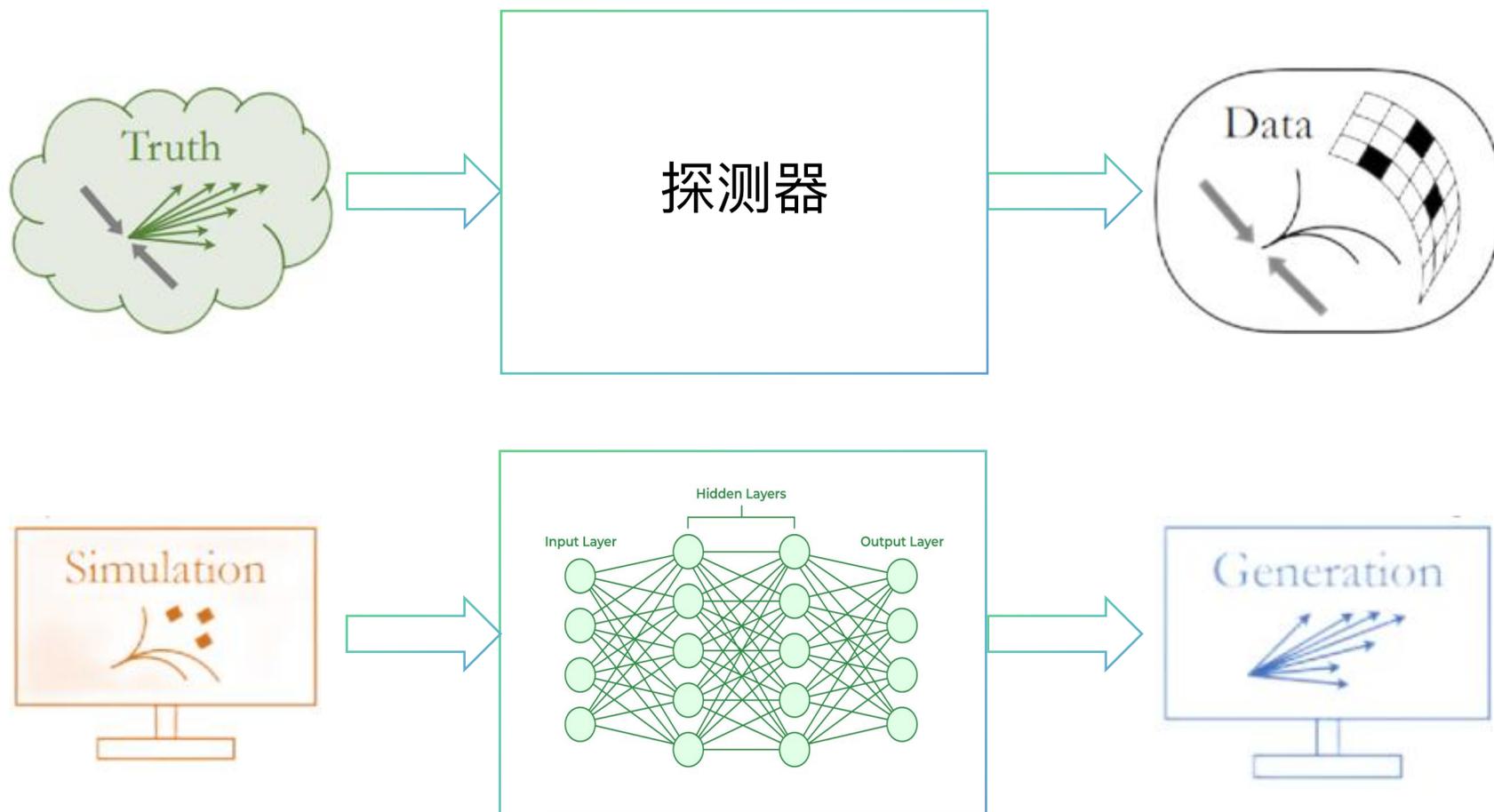
建立探测器的“世界模型”是可能的!



# 探测器模拟+AI



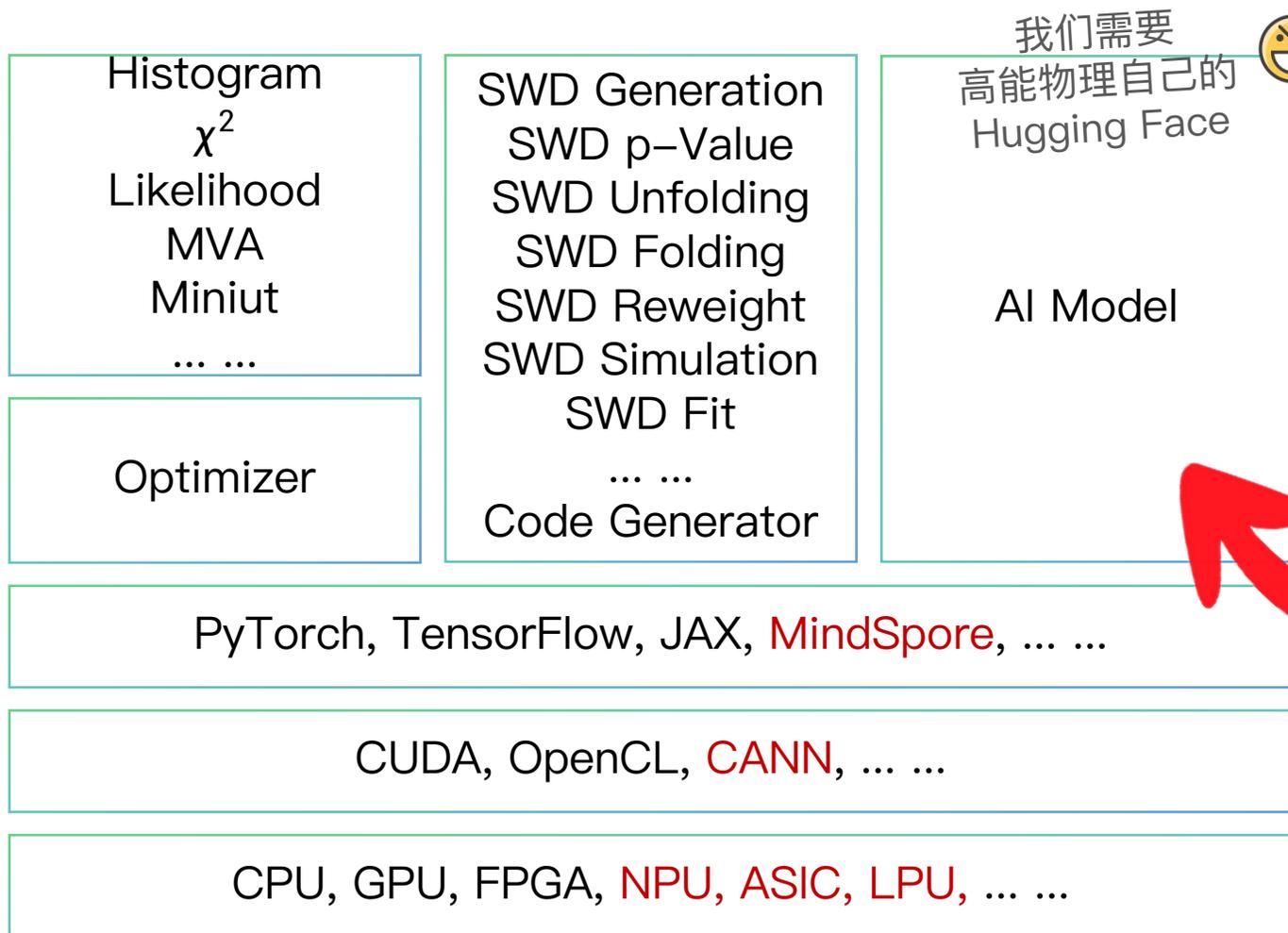
# 探测器模拟+AI



## 建立探测器神经网络模型的意义:

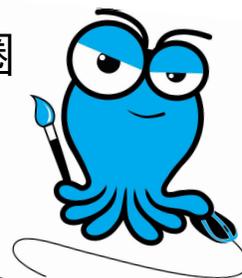
- 高精度的快速模拟;
- 节省大量存储空间;
- 可以充分利用神经网络的反向传播特性, 通过Data直接对Truth提供约束;
- 建立探测器模型需要“由简到繁”。

# 数据分析工具+AI



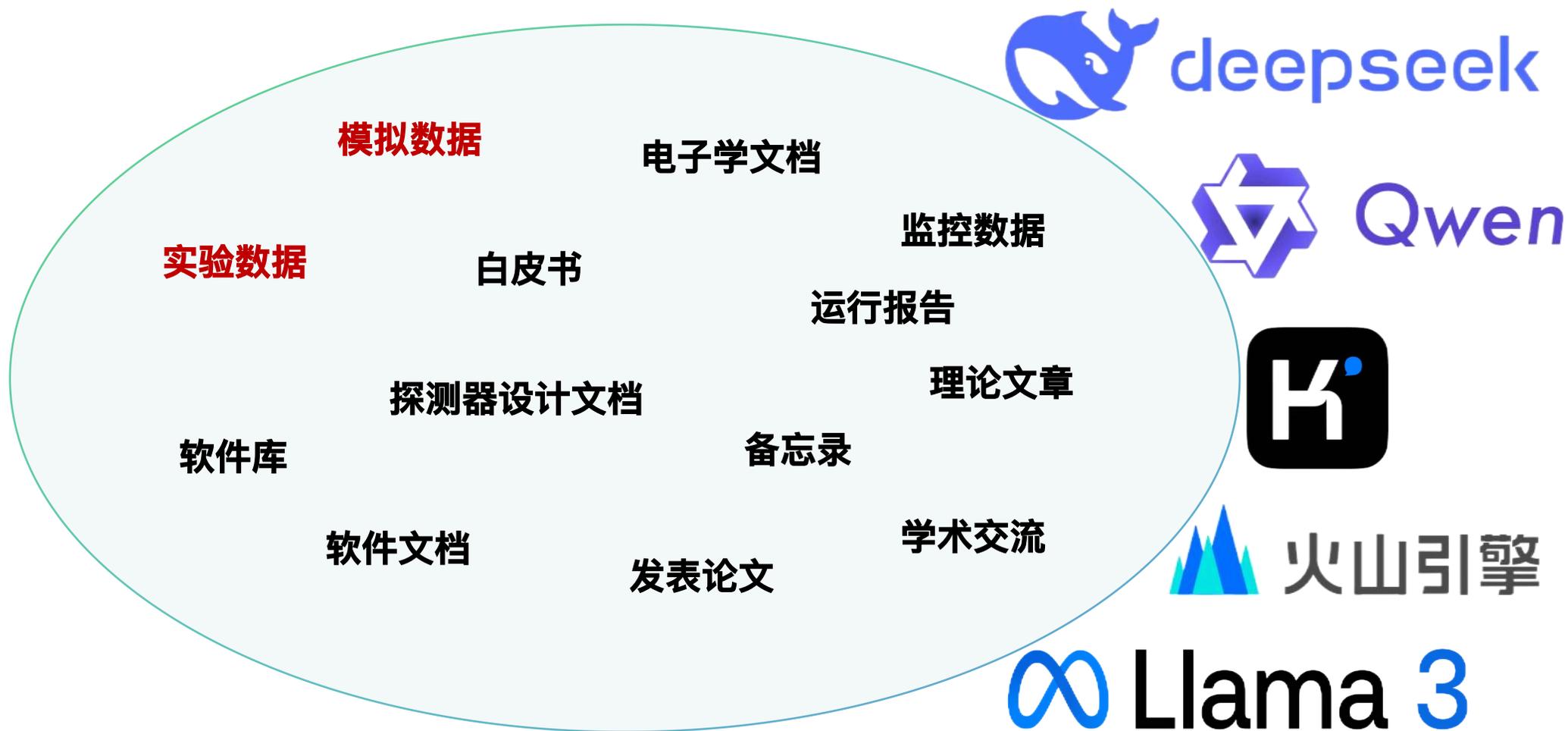
## 数据分析+AI实现方式:

- 打通现有工具的AI接口;
- 融合AI的数据分析范式;
- 建立适合特定任务的AI Agent;
- 形成AI Agents生态圈



Creative Agency

# 高能物理实验+LLM



# 智能化电子学设备管理系统

江门电子智能化管理系统  
低压电源探测器集群数据分析平台

系统状态  
● 运行正常

## 时间段选择与报告生成

开始时间

2025/07/01 上午12:00

结束时间

2025/07/01 上午01:00

探测器集群

集群A - 电子学间01

生成报告

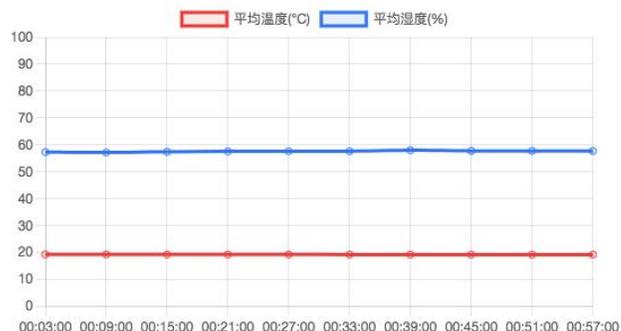
总探测器数量  
10260

正常运行  
9621

异常警告  
639

离线设备  
0

## 电压趋势分析



## 设备状态分布



## 分析总结

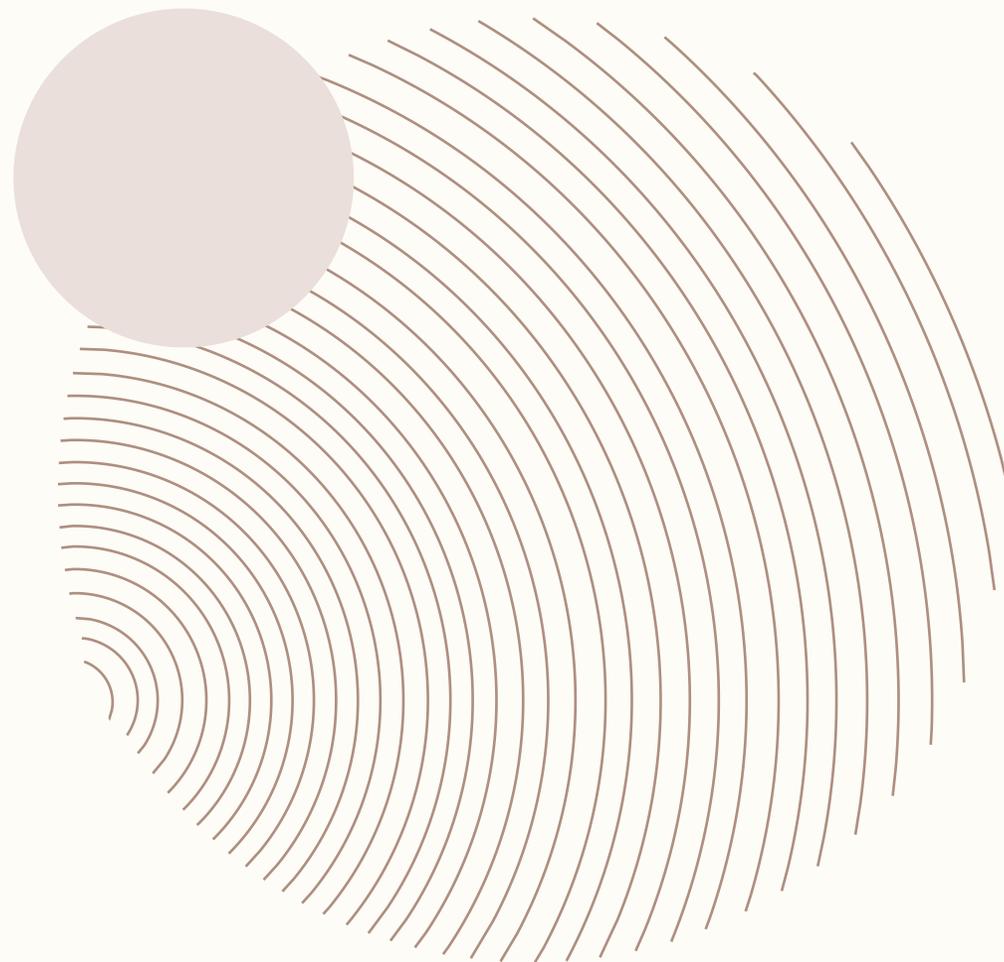
好的，收到。作为一名资深数据分析师，我将对您提供的低压电源（LVP）监控异常数据进行分析，并生成一份专业的报告。

- 通过大语言模型理解设备监控数据；
- 通过长期积累，争取在电子学失效机制等方面取得研究进展。

# 小结

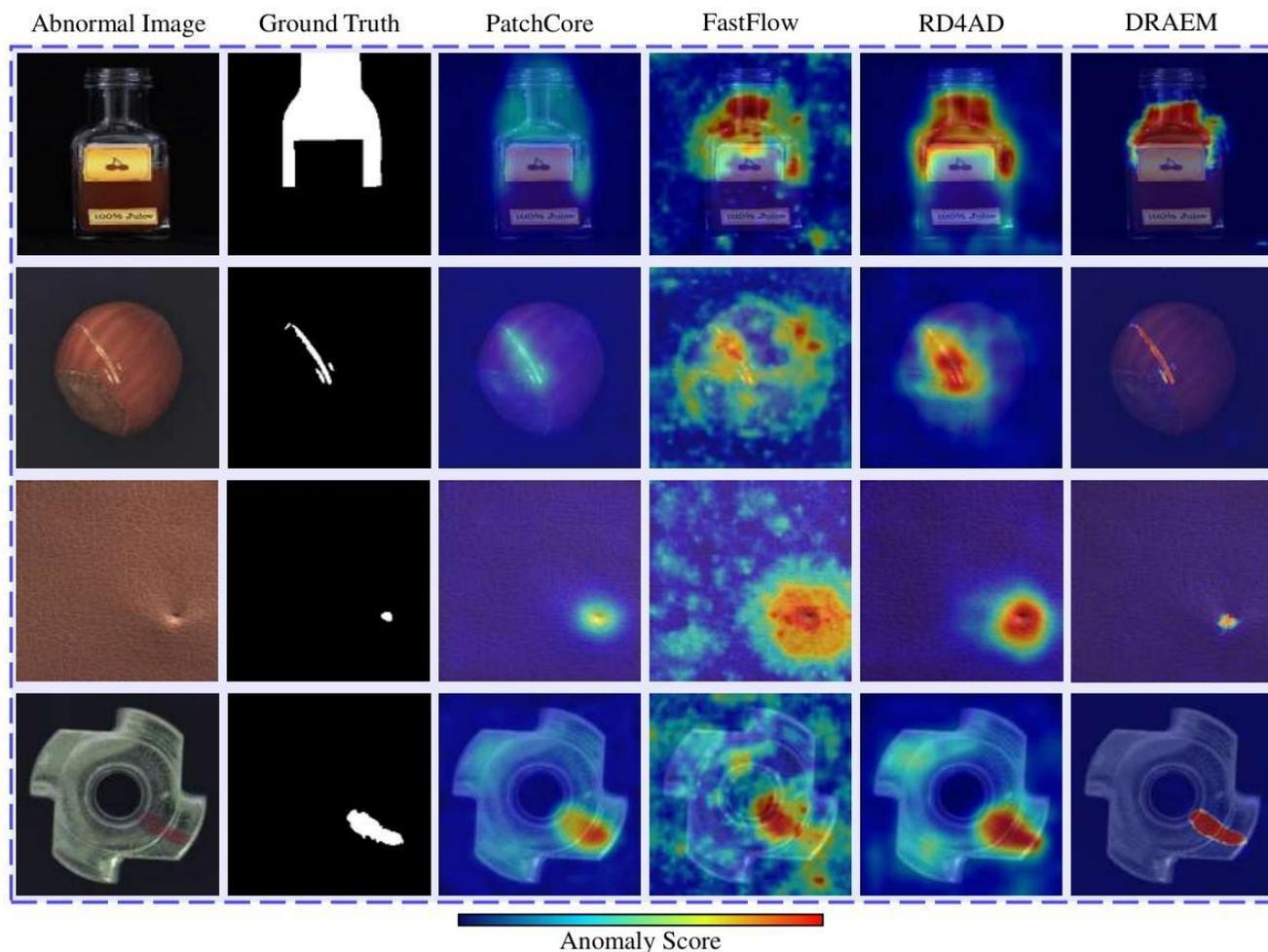
- SWD作为一种计算/评估高能物理数据分布一致性的新方法，将对高能物理实验产生深远影响；
- SWD创造了开发深度融合AI的高能物理数据分析工具的机会窗口；
- AI的快速发展对于高能物理实验来说既是机遇也是挑战。

# 工业缺陷检测现状



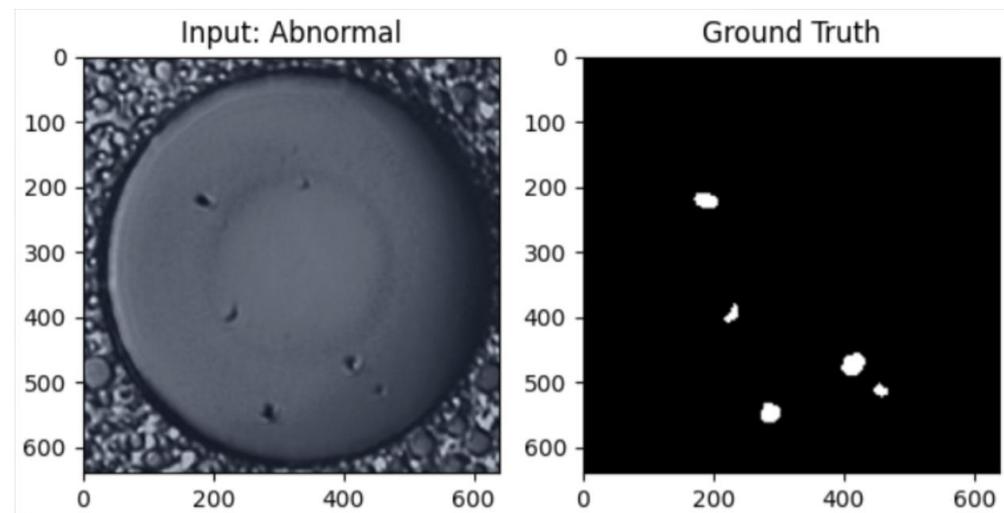
# 缺陷监测研究背景与意义

- 核心问题：工业图像异常检测（IAD）的定义 —— 识别产品缺陷以保障质量。
- 传统人工检测的局限性：
  - 无法避免疲劳导致的假阳性（真实异常被误判为正常）；
  - 长期工作引发视觉损伤等健康问题；
  - 需大量人力，运营成本高。
- 深度学习的优势：准确率极大提高，减少人力并提升效率。

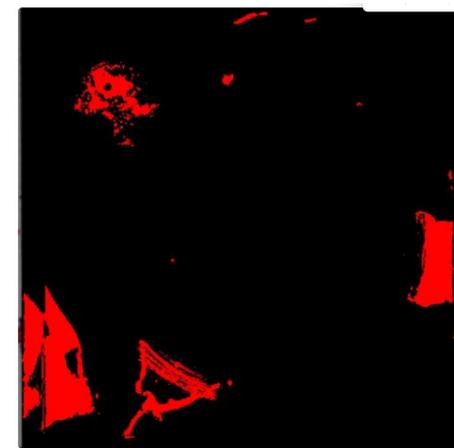
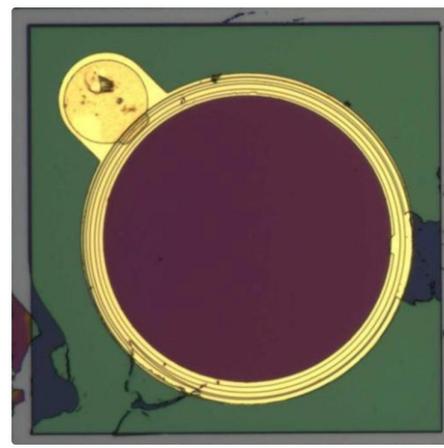
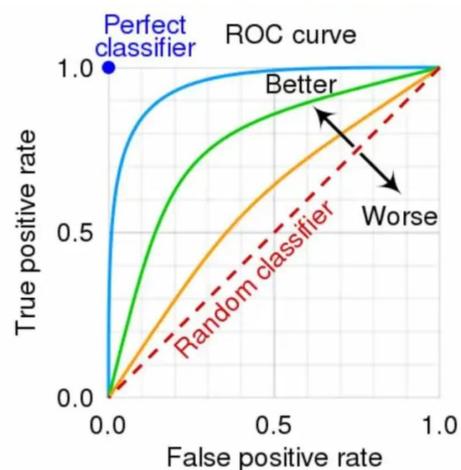


# 现有研究的不足

- 数据集问题：开源数据多非真实生产线生成，异常样本与实际不符；
- 模型局限性：缺乏跨域统一模型，现有数据集（如 MVTEC AD）无多域数据；
- 评估指标缺陷：指标精度损失，需统一图像级和像素级评估。



光纤端面/芯片数据集



# 核心挑战

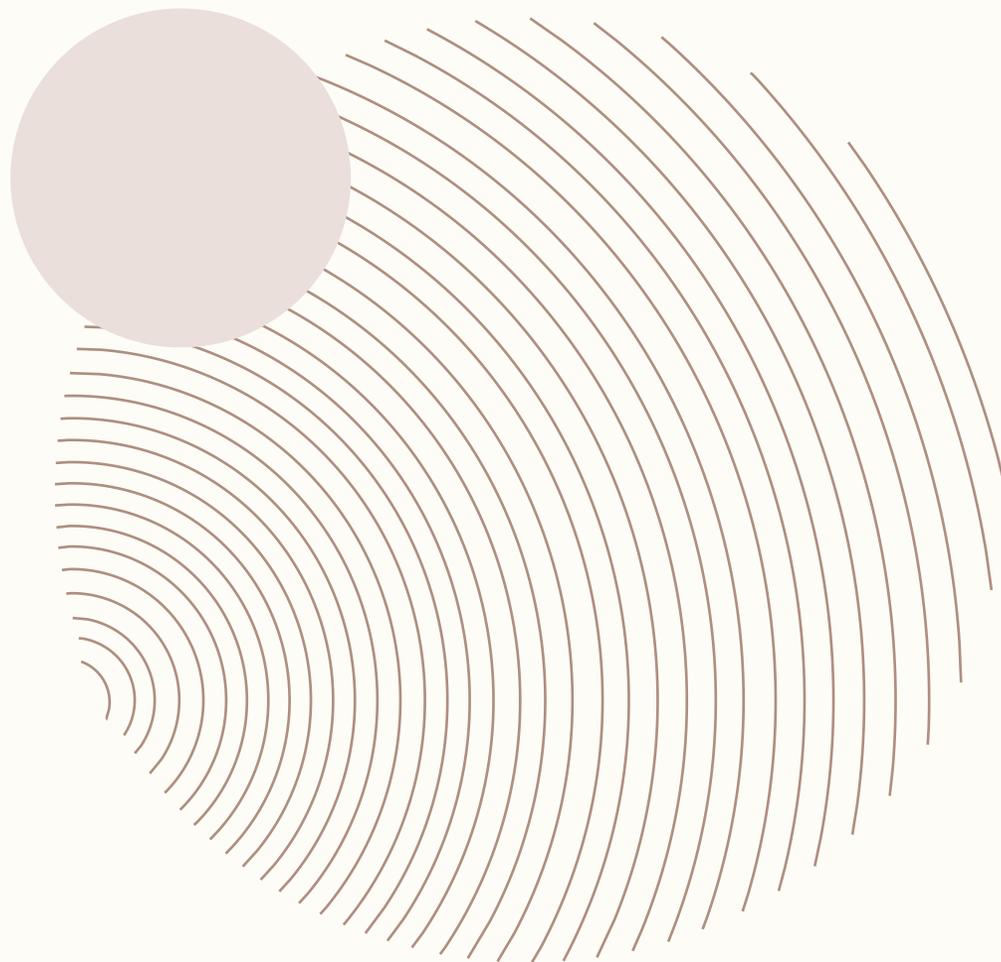
- 数据集真实性：真实异常数据因隐私难以获取；
- 跨域泛化：同一工厂多类工件检测需统一模型；
- 模型创新：需平衡有标签与无标签数据利用。



武汉光迅科技股份有限公司

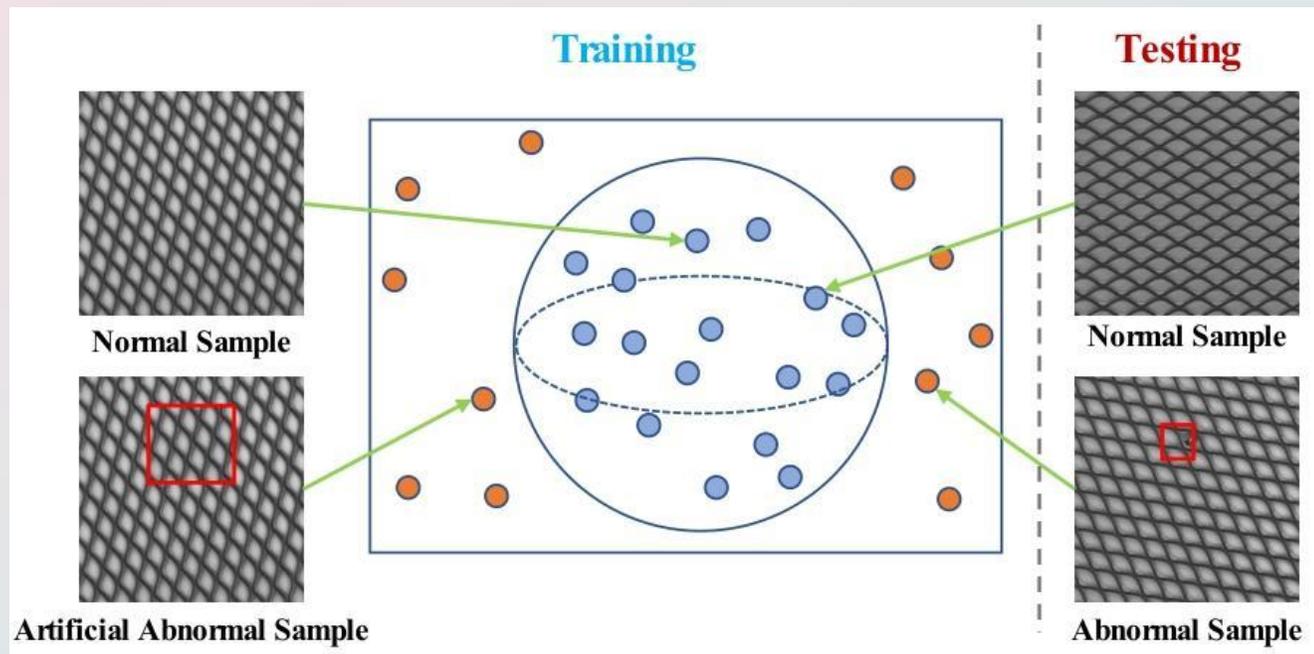


# 无监督缺陷检测方法

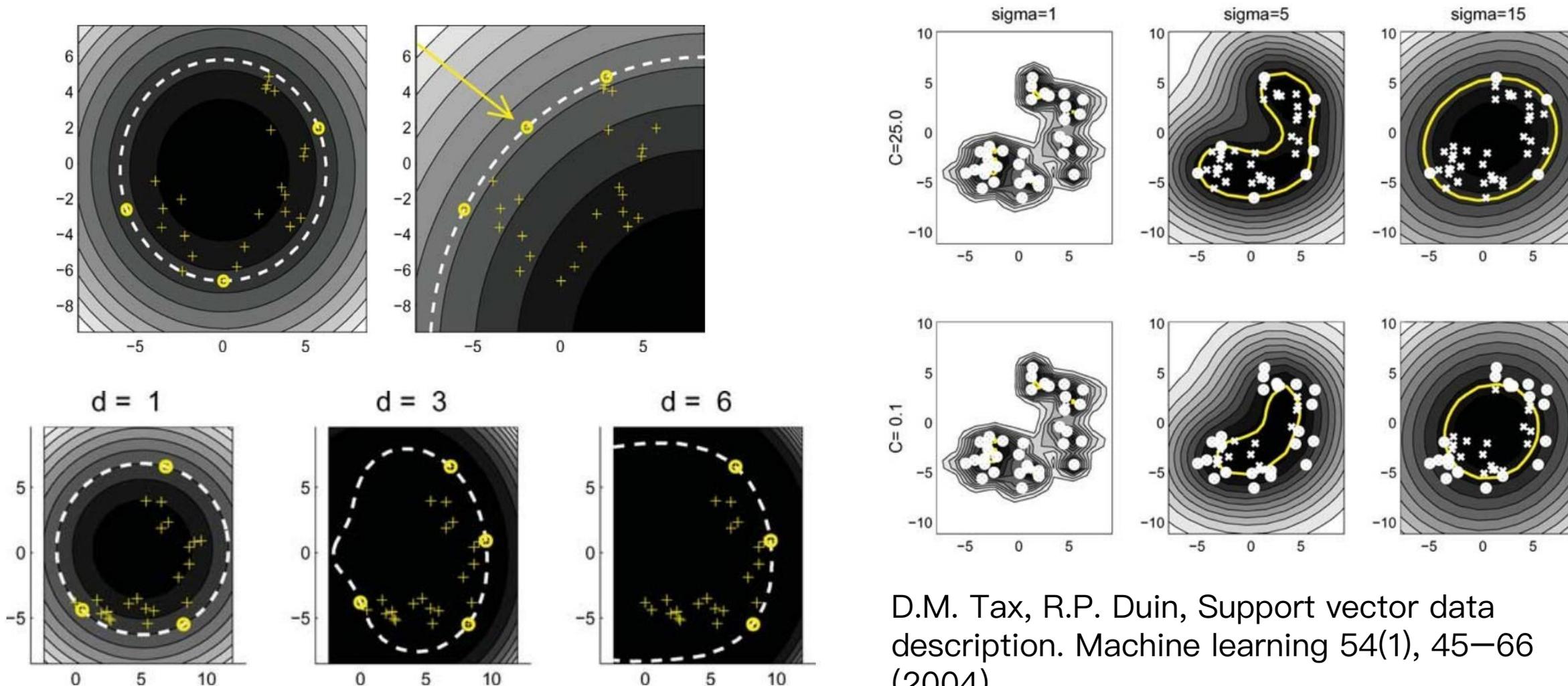


# 单类分类 (One-Class Classification)

- 通过 hypersphere 划分正常 / 异常特征空间
- 核心目标是仅通过大量正常样本学习“正常模式的边界”（如用超球面、特征分布范围定义正常样本的范围），从而区分异常样本。但实际应用中，**这类技术往往更依赖异常样本（即使是人工生成的异常样本）**

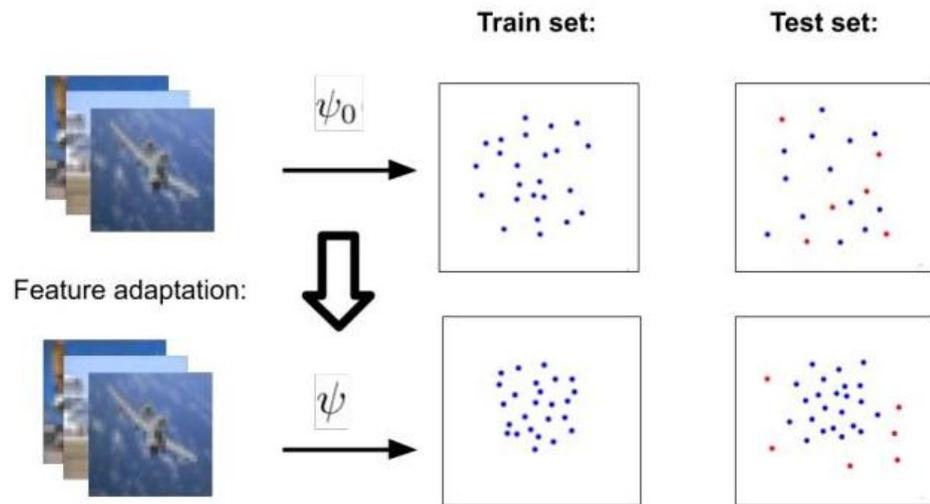


# SVDD: 支持向量数据描述方法

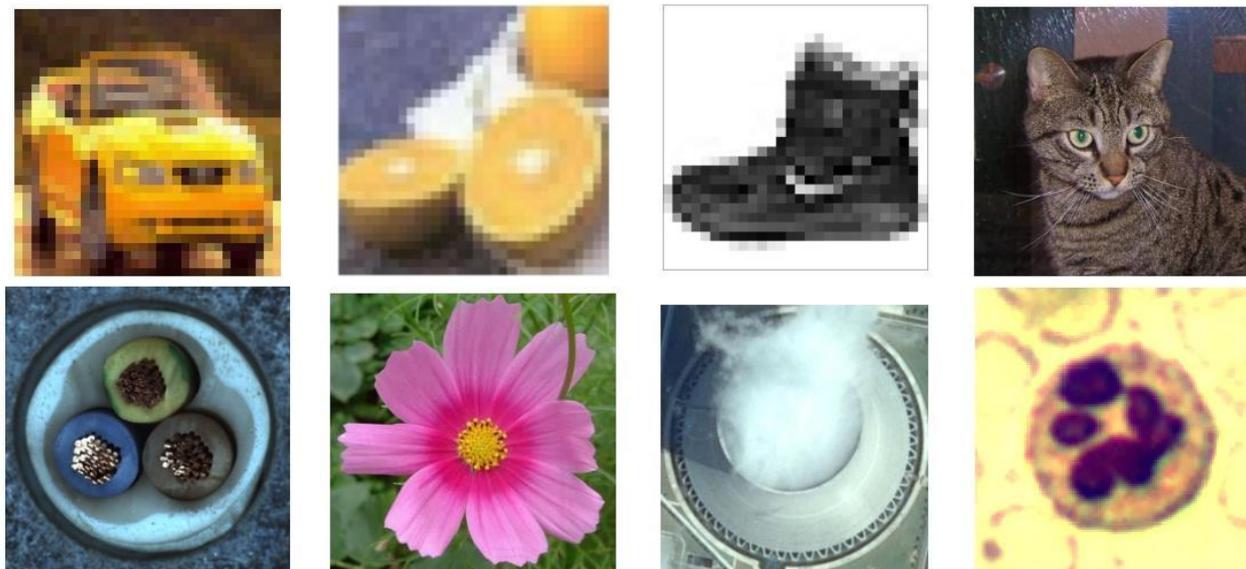
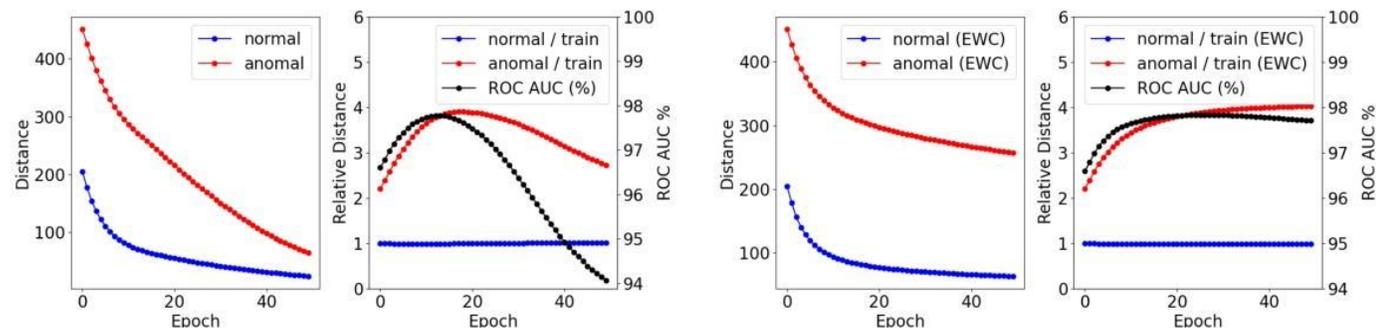


D.M. Tax, R.P. Duin, Support vector data description. Machine learning 54(1), 45–66 (2004)

# PANDA: 将预训练特征适配于异常检测与分割



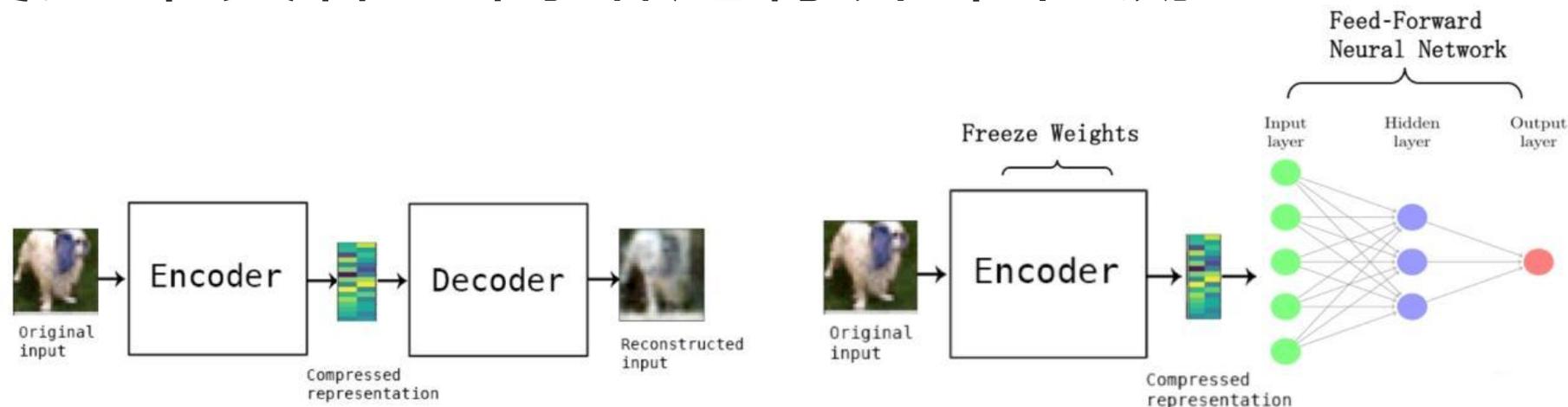
$$L_{compact} = \sum_{x \in \mathcal{D}_{train}} \|\psi(x) - c\|^2$$



T. Reiss, N. Cohen, L. Bergman, Y. Hoshen,  
 Panda: Adapting pretrained features for  
 anomaly detection and segmentation.  
 Proceedings of the IEEE/CVF Conference on  
 Computer Vision and Pattern Recognition pp.  
 2806–2814 (2021)

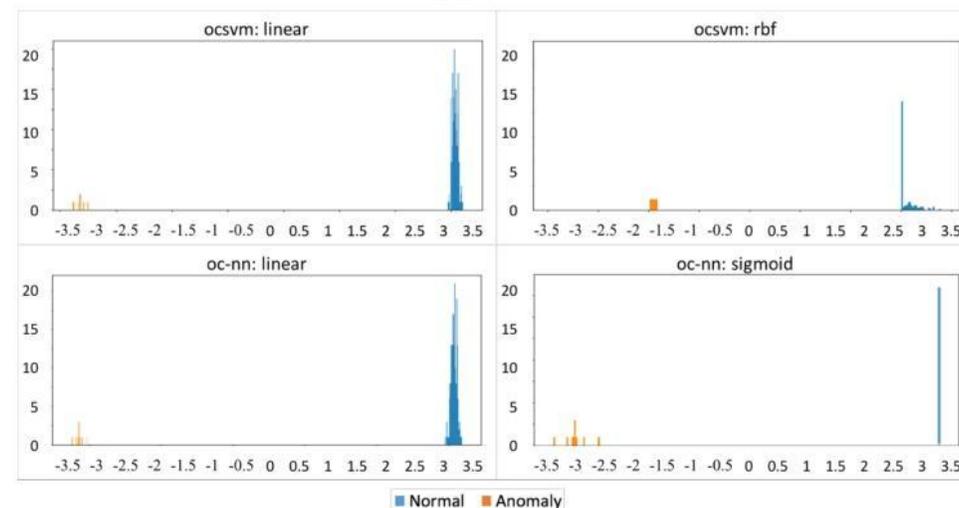
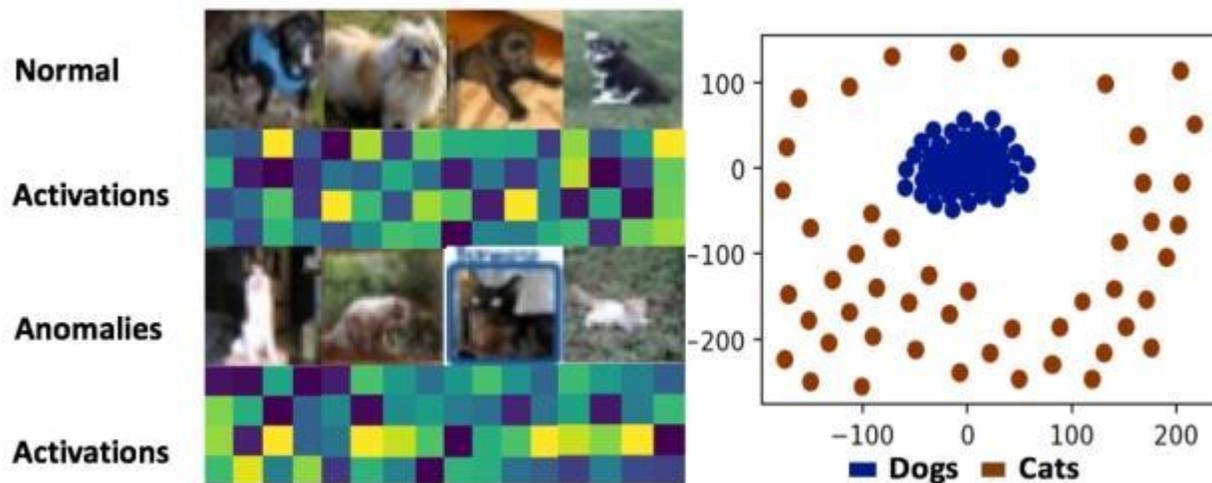
# OC-NN: 使用单类神经网络进行异常检测

Chalapathy, R., et al. (2018). Anomaly Detection using One-Class Neural Networks.



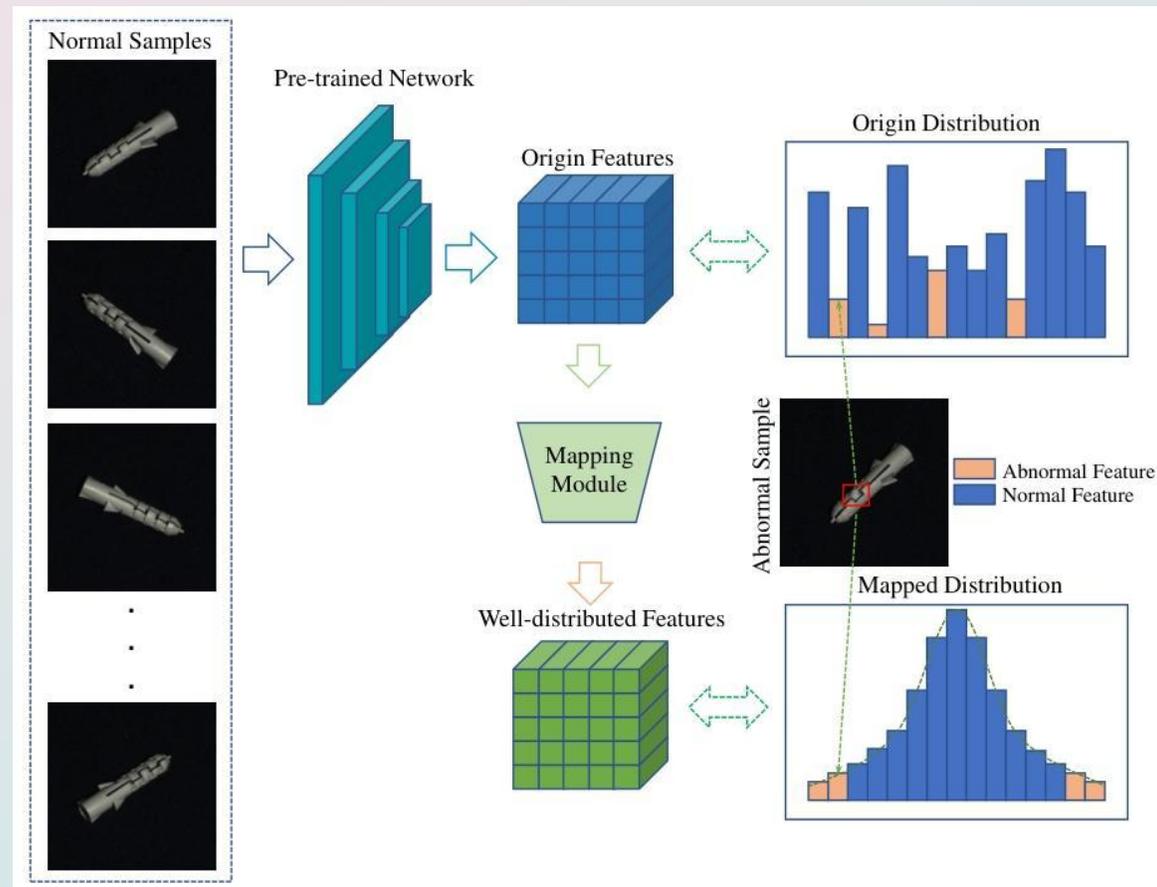
(a) Autoencoder .

(b) one-class neural networks.

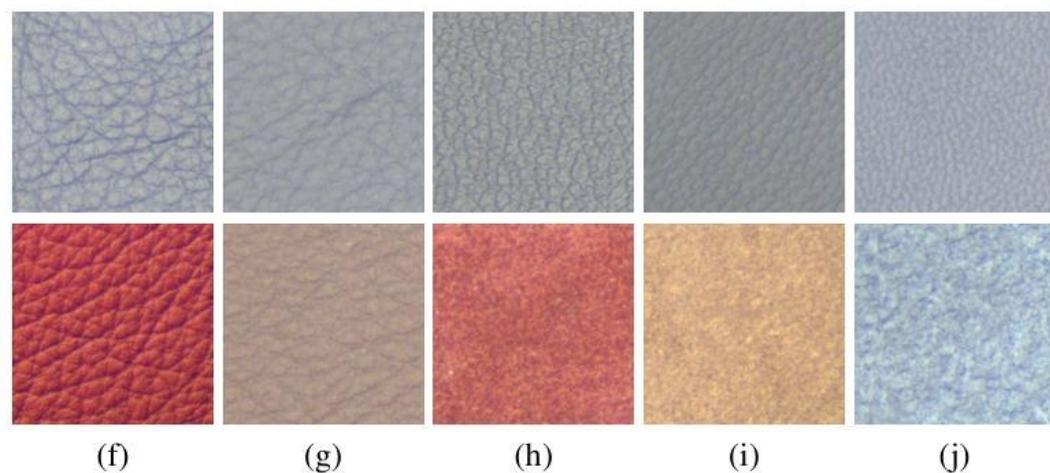
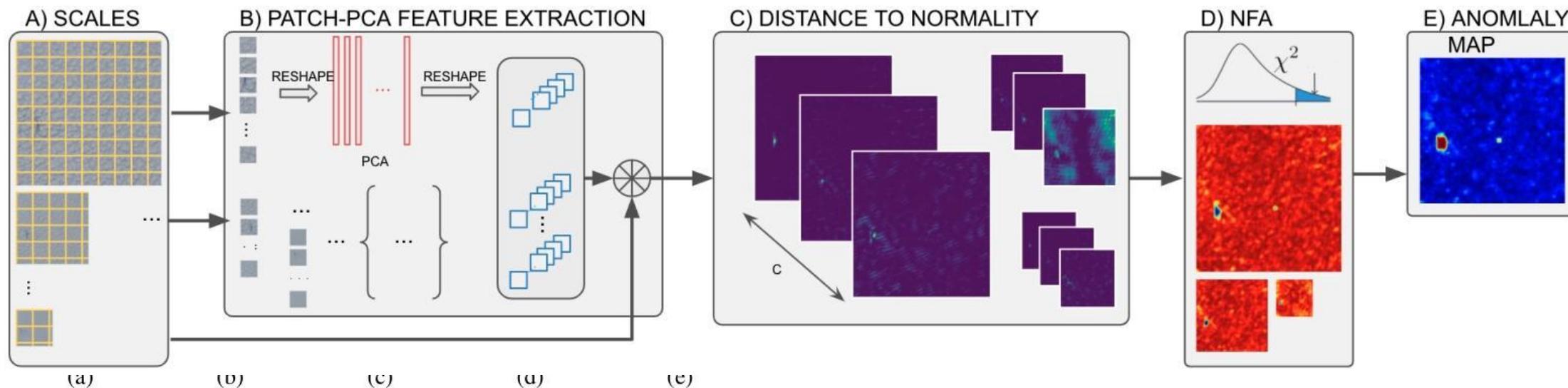


# 分布映射 (Distribution Map)

- 将正常特征映射到目标分布（如高斯分布），异常特征偏离该分布
- Distribution Map 方法通过将正常样本特征映射到目标分布（如多元高斯分布、归一化流模型）来描述“正常”，不依赖明确的特征边界，对特征分布的假设更灵活，能适应工业场景中多模态、非凸等复杂的正常样本特征分布（如不同批次产品的微小外观差异）
- 通过建模正常特征的概率密度，能更精细地刻画正常样本的统计特性，对未见过的异常类型（如新型缺陷）更敏感，泛化性更强

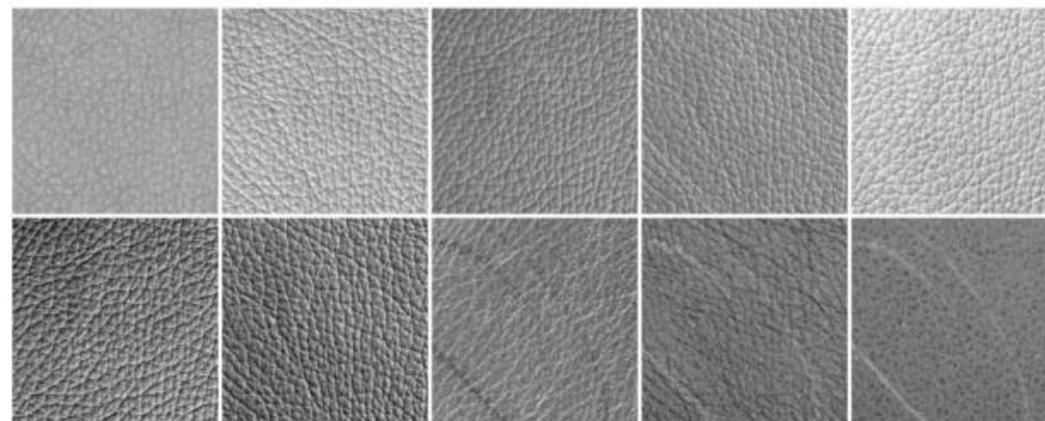
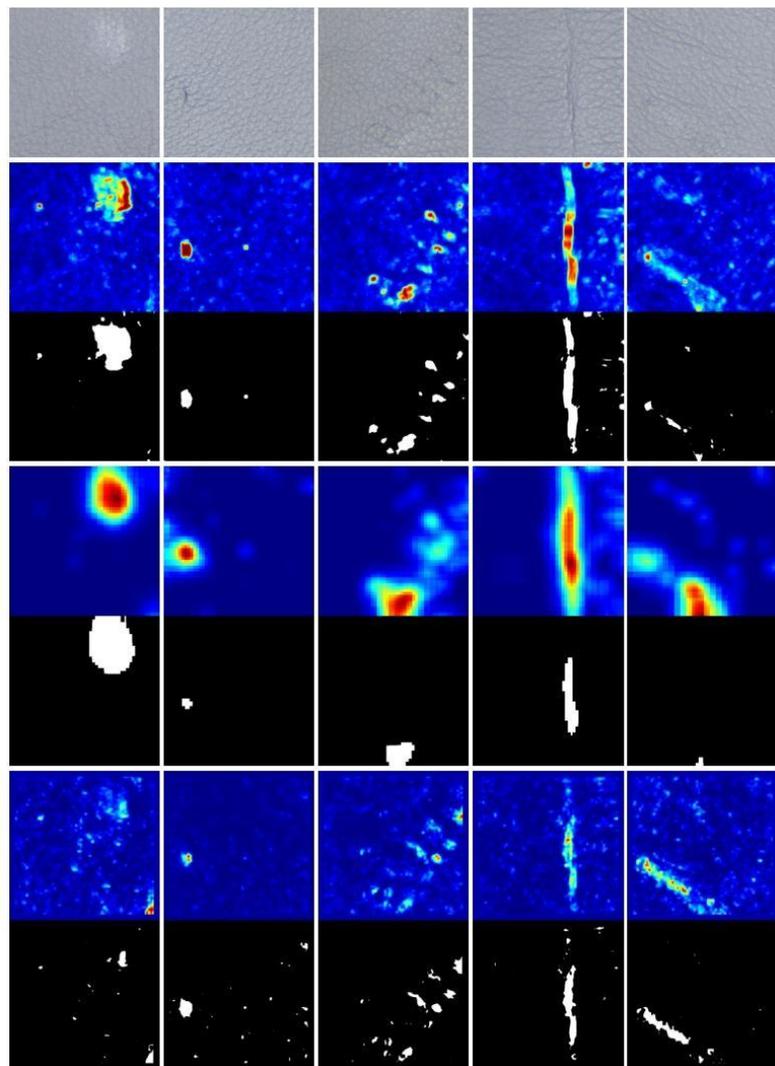


# NFA-MAP: 无监督图像异常检测的多尺度反证法



M. Tailanián, P. Musé, A. Pardo, A multi-scale a contrario method for unsupervised image anomaly detection. 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA) pp. 179–184 (2021)

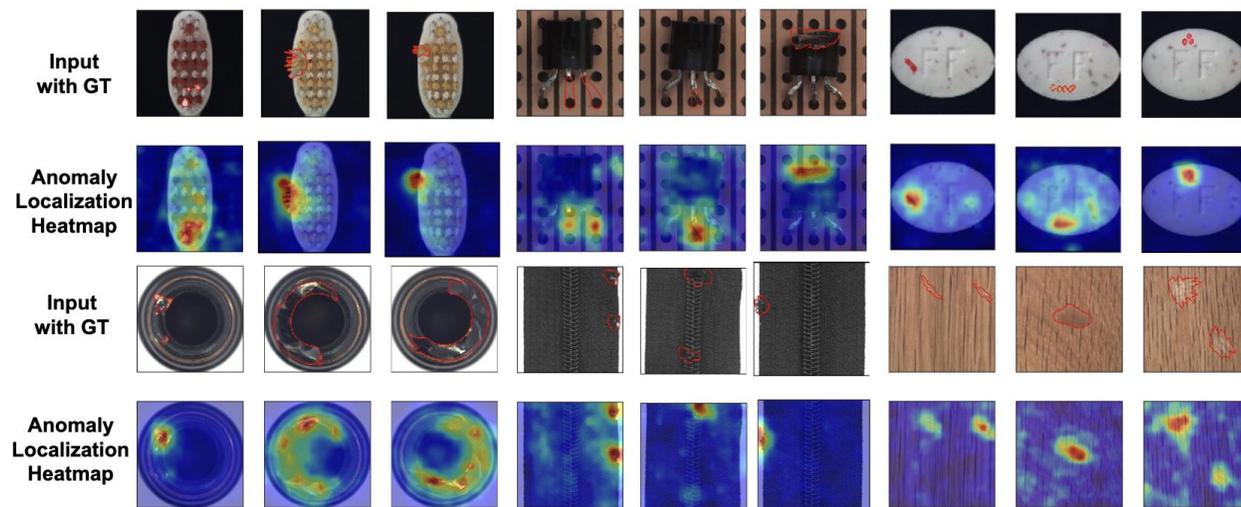
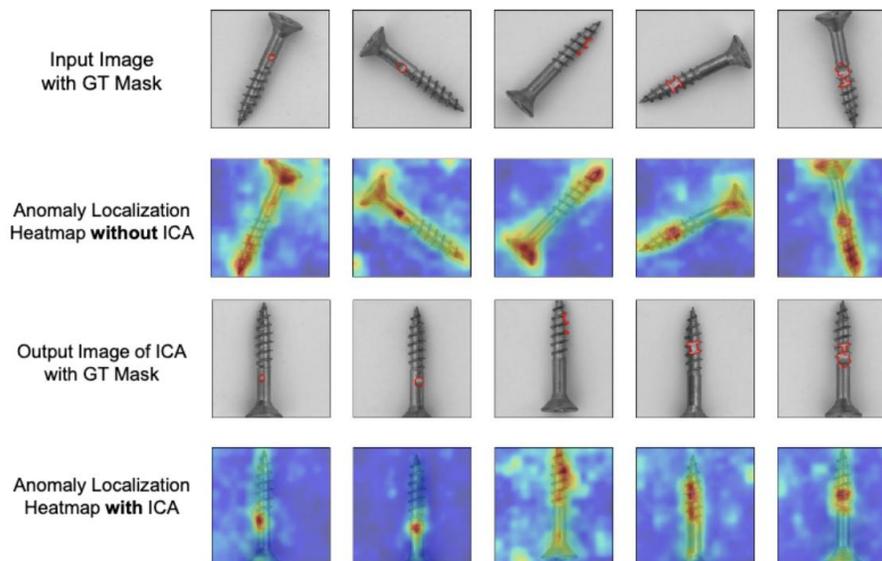
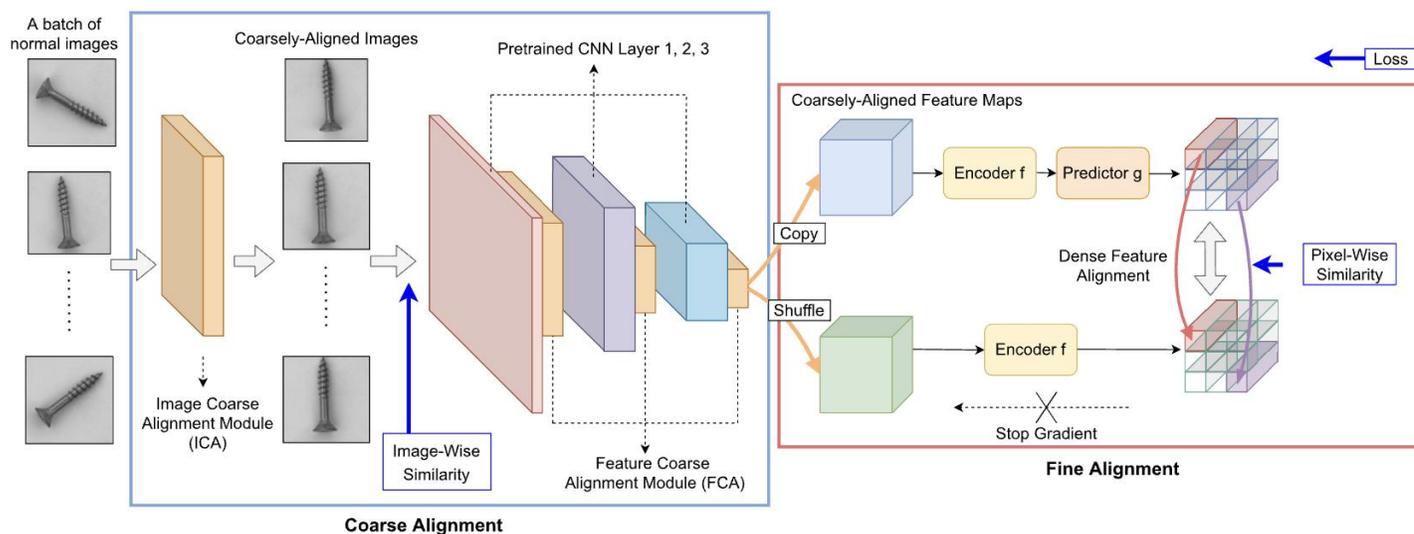
# NFA-MAP: 无监督图像异常检测的多尺度反证法



PCA处理后的图像

*Fig. 6. Results on our industrial data. First row: original diffuse image. Following rows show the anomaly score map and the segmentation with  $AS=0$ , for three variants of our proposed method: PCA+PixelNFA, Gabor+BlockNFA, and ResNer+PixelNFA. All defects are detected in all cases, and ( $AS=0$ ) provides a good choice for the detection threshold.*

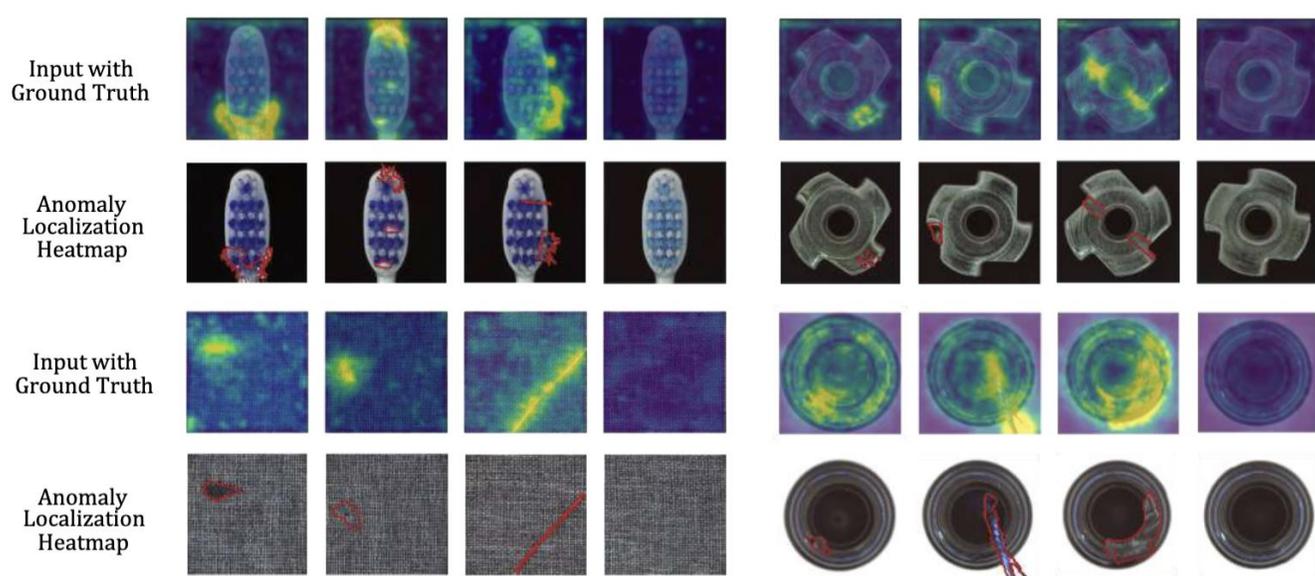
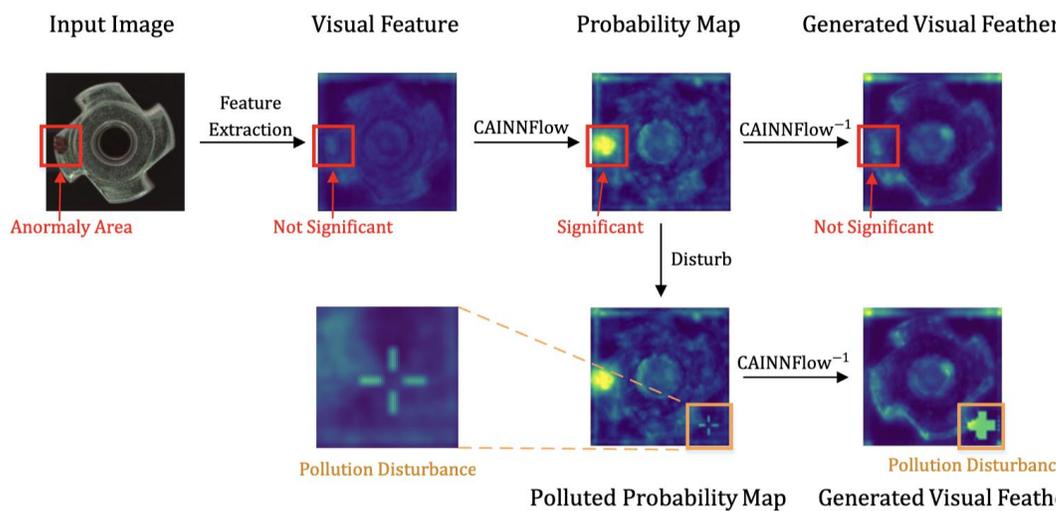
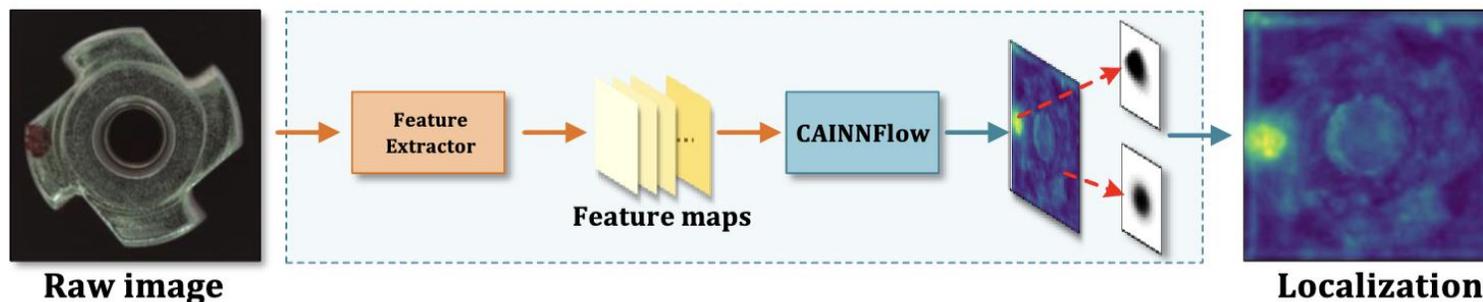
# FYU: 用于异常检测与定位的从粗到细非对比学习



Y. Zheng, X. Wang, R. Deng, T. Bao, R. Zhao, L. Wu, Focus your distribution: Coarse-to-fine non-contrastive learning for anomaly detection and localization. 2022 IEEE International Conference on Multimedia and Expo (ICME) pp. 1–6 (2022)

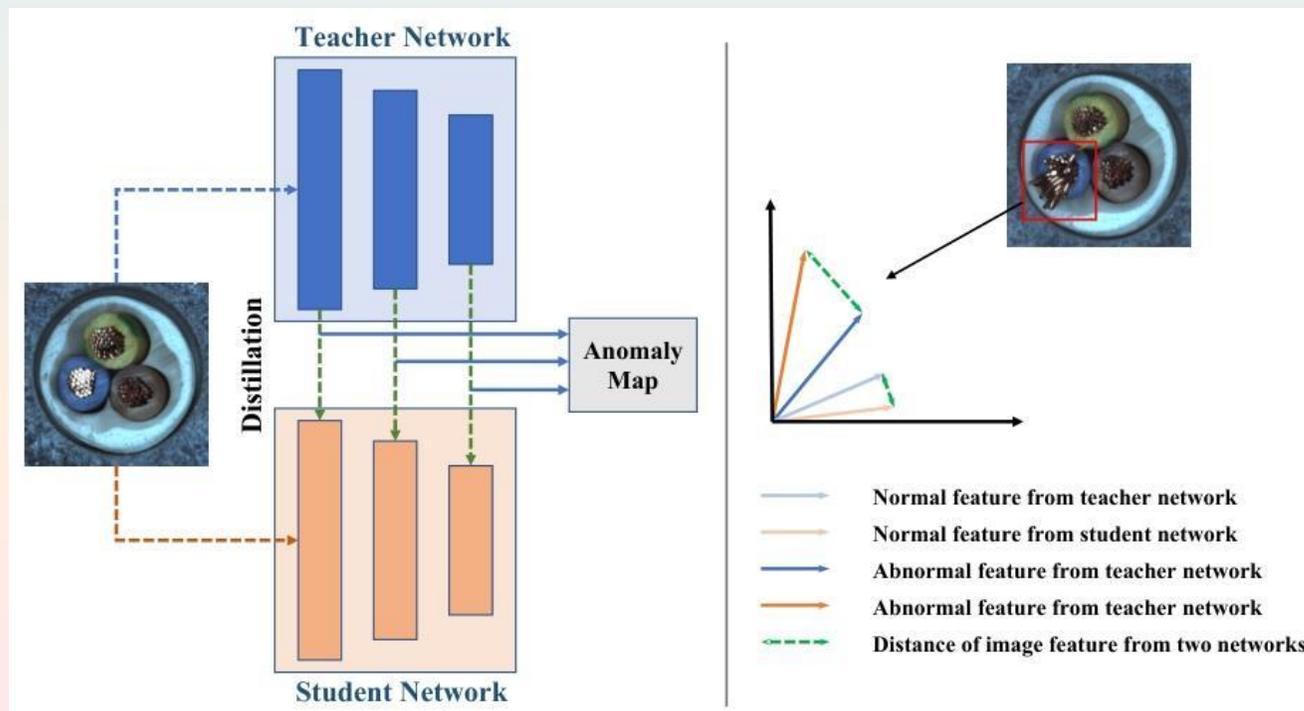
# CAINNFlow: 用于异常检测与定位任务的卷积块注意力模块和可逆神经网络流

R. Yan, F. Zhang, M. Huang, W. Liu, D. Hu, J. Li, Q. Liu, J. Jiang, Q. Guo, L. Zheng, Cainnflow: Convolutional block attention modules and invertible neural networks flow for anomaly detection and localization tasks. arXiv preprint arXiv:2206.01992 (2022)

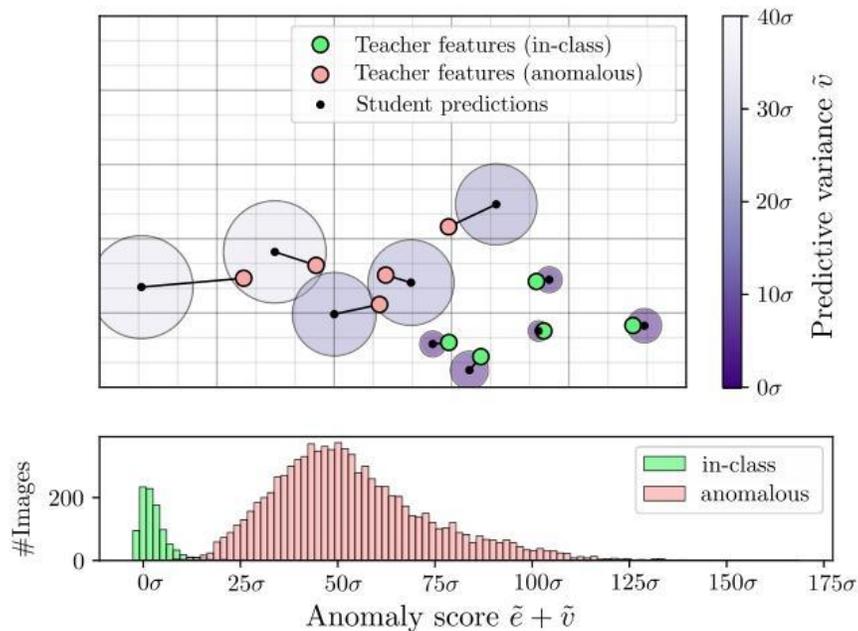
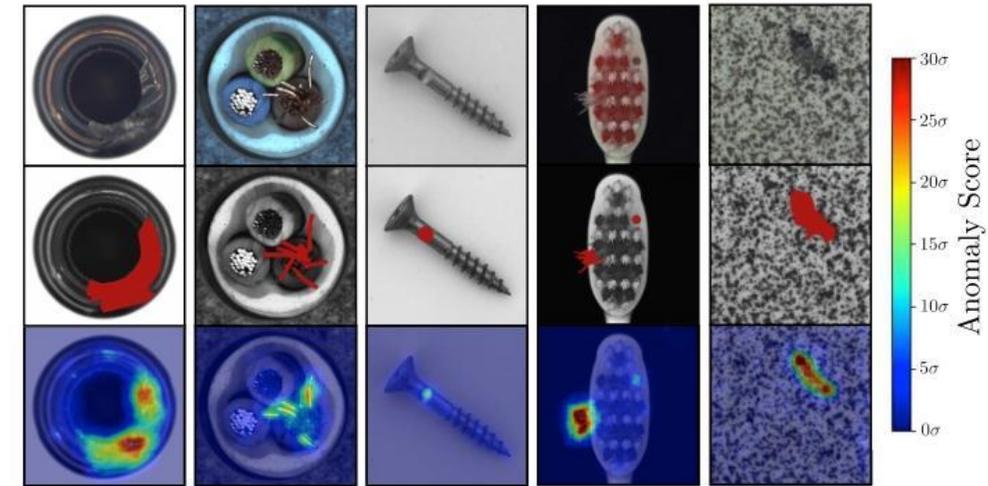
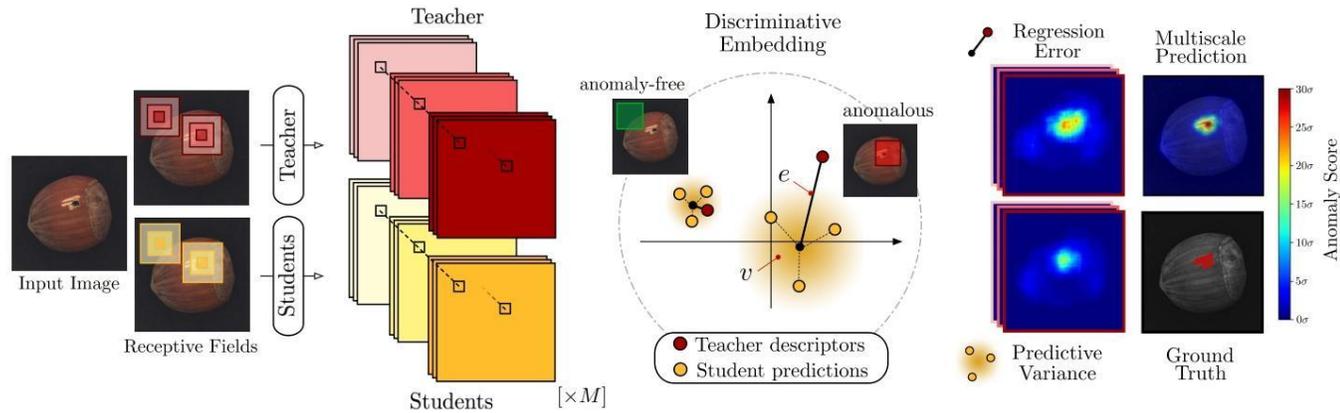


# 师生架构 (Teacher-Student)

- 教师模型 (预训练) 教学生模型提取正常特征, 通过特征差异检测异常
- 教师模型通常在通用数据集 (如 ImageNet) 上训练, 可能与工业场景的特征分布存在偏差, 模型提取的通用特征可能无法捕捉工业缺陷的细微模式, 导致对新型缺陷的漏检

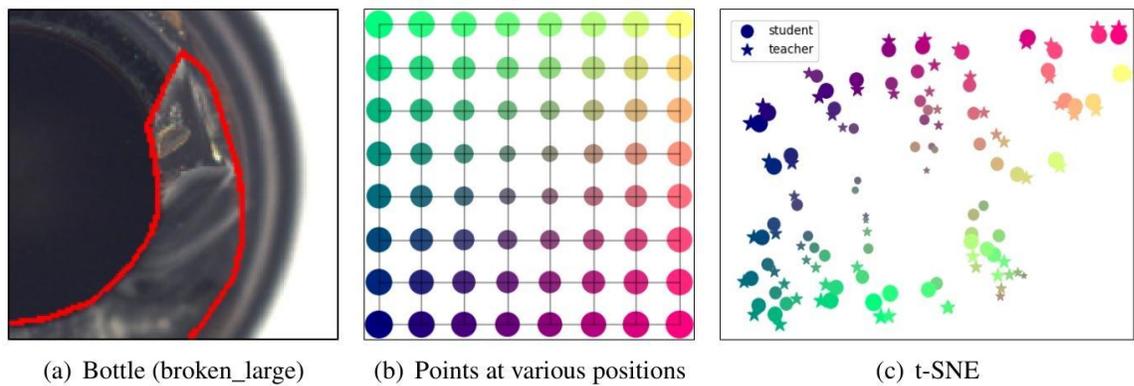
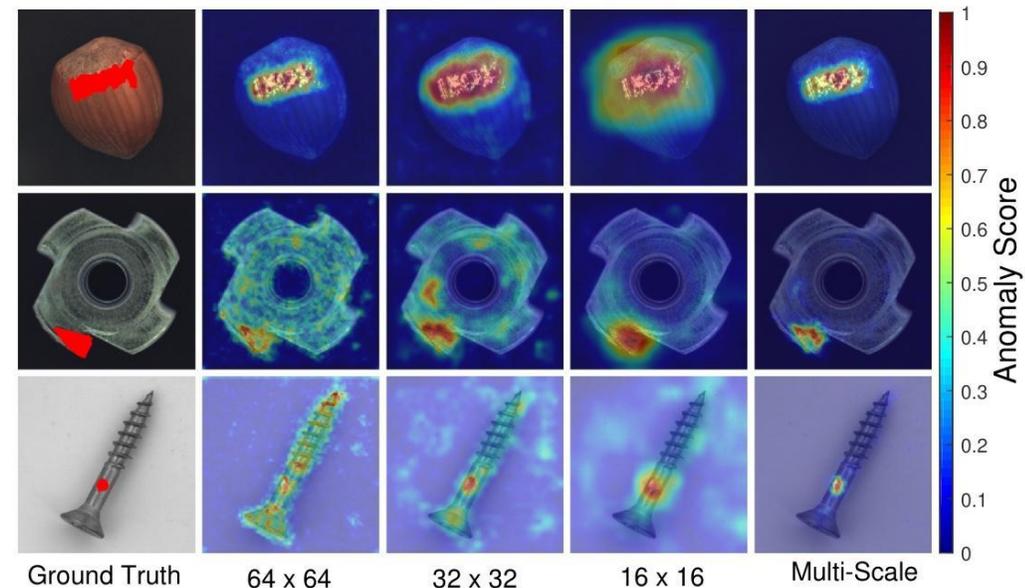
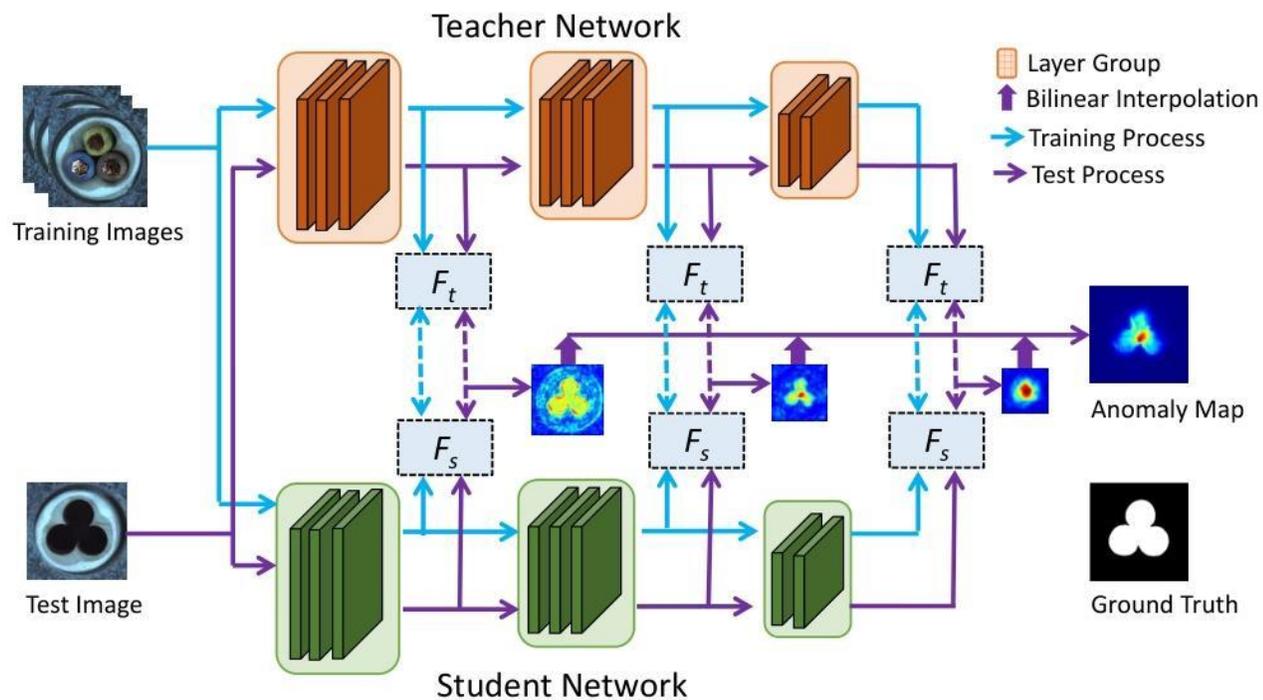


# Uninformed students



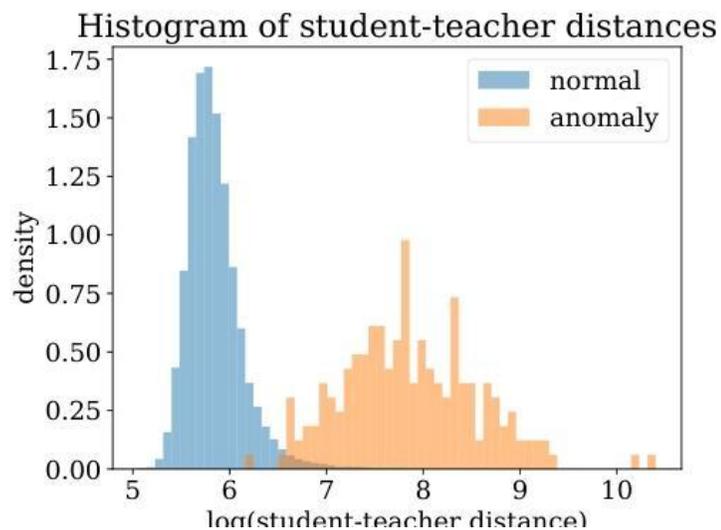
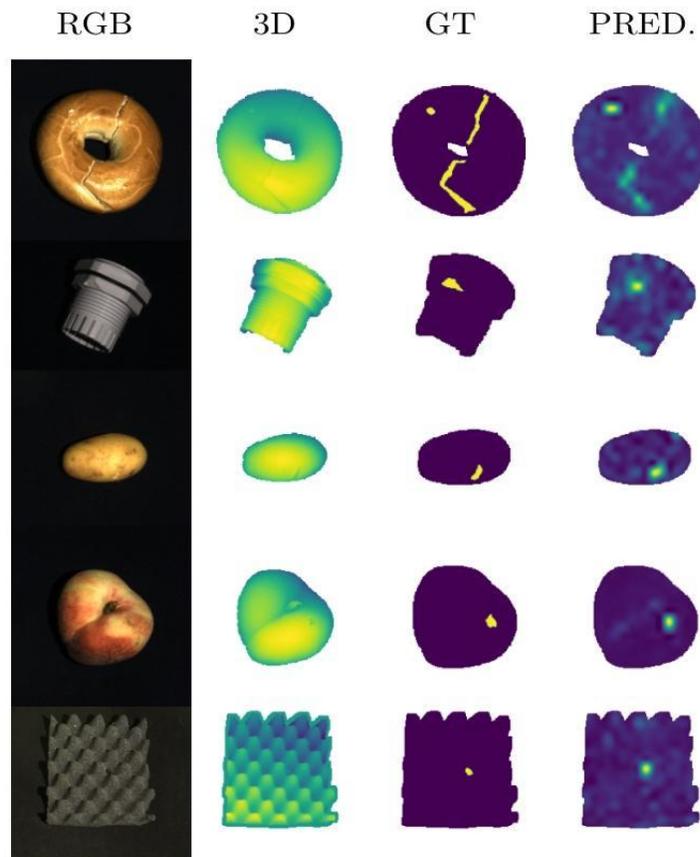
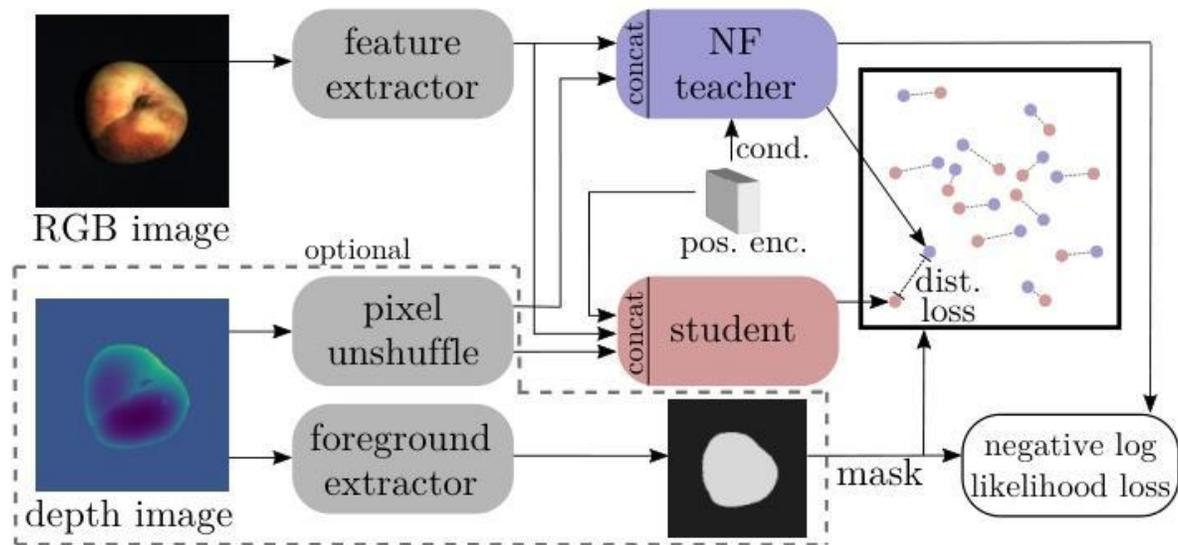
P. Bergmann, M. Fauser, D. Sattlegger, C. Steger, Uninformed students: Student–teacher anomaly detection with discriminative latent embeddings. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition pp. 4183–4192 (2020)

# STPM: 多尺度特征蒸馏



P. Bergmann, K. Batzner, M. Fauser, D. Sattlegger, C. Steger, Beyond dents and scratches: Logical constraints in unsupervised anomaly detection and localization. International Journal of Computer Vision 130(4), 947–969 (2022)

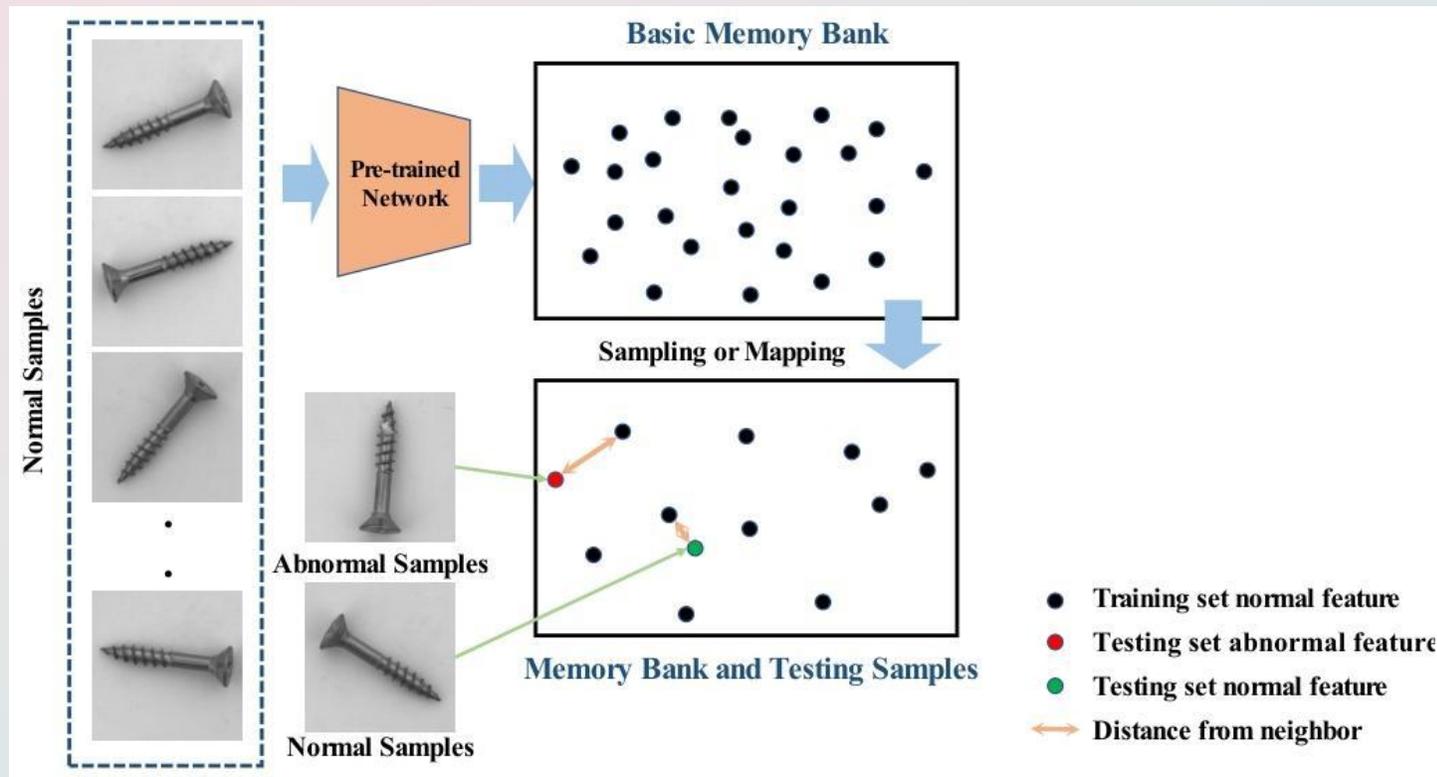
# AST: 非对称架构增强异常差异



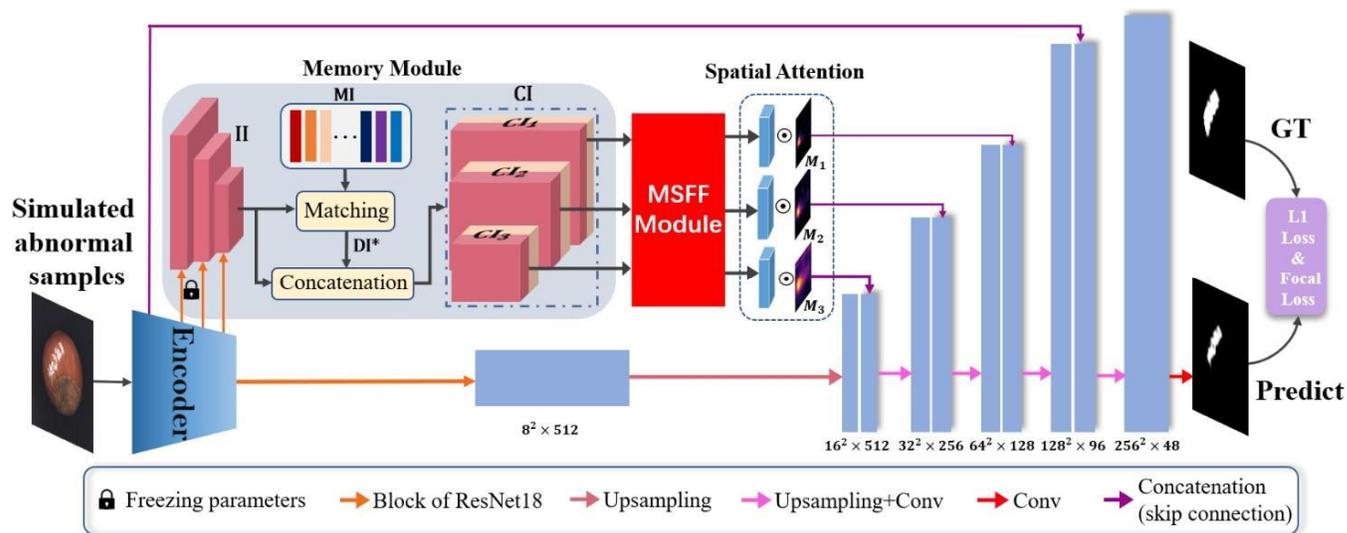
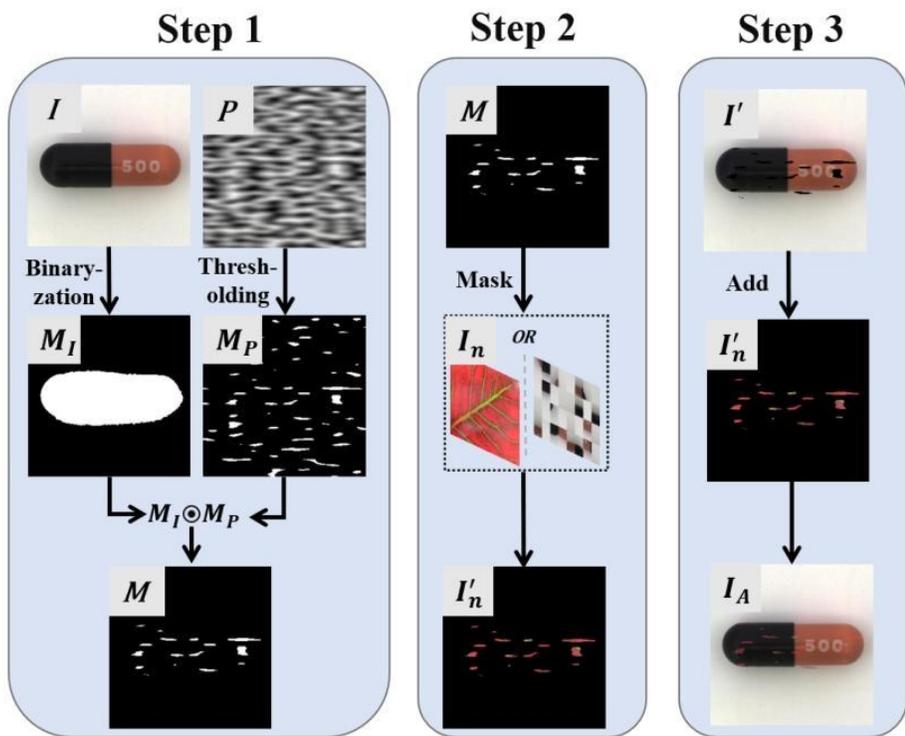
M. Rudolph, T. Wehrbein, B. Rosenhahn, B. Wandt, Asymmetric student-teacher networks for industrial anomaly detection. arXiv preprint arXiv:2210.07829 (2022)

# 记忆库 (Memory Bank)

- Memory Bank 是工业图像异常检测中一种高效的无监督学习方法，其核心思想是通过存储正常样本的特征，在推理阶段通过对比测试样本与记忆库中特征的差异来识别异常
- 无需训练复杂网络，仅需构建记忆库，推理速度快；通过存储多样化的正常特征，对细微变化（如不同批次产品的微小差异）适应性强；轻量级设计，适合边缘设备，降低工业场景的计算成本

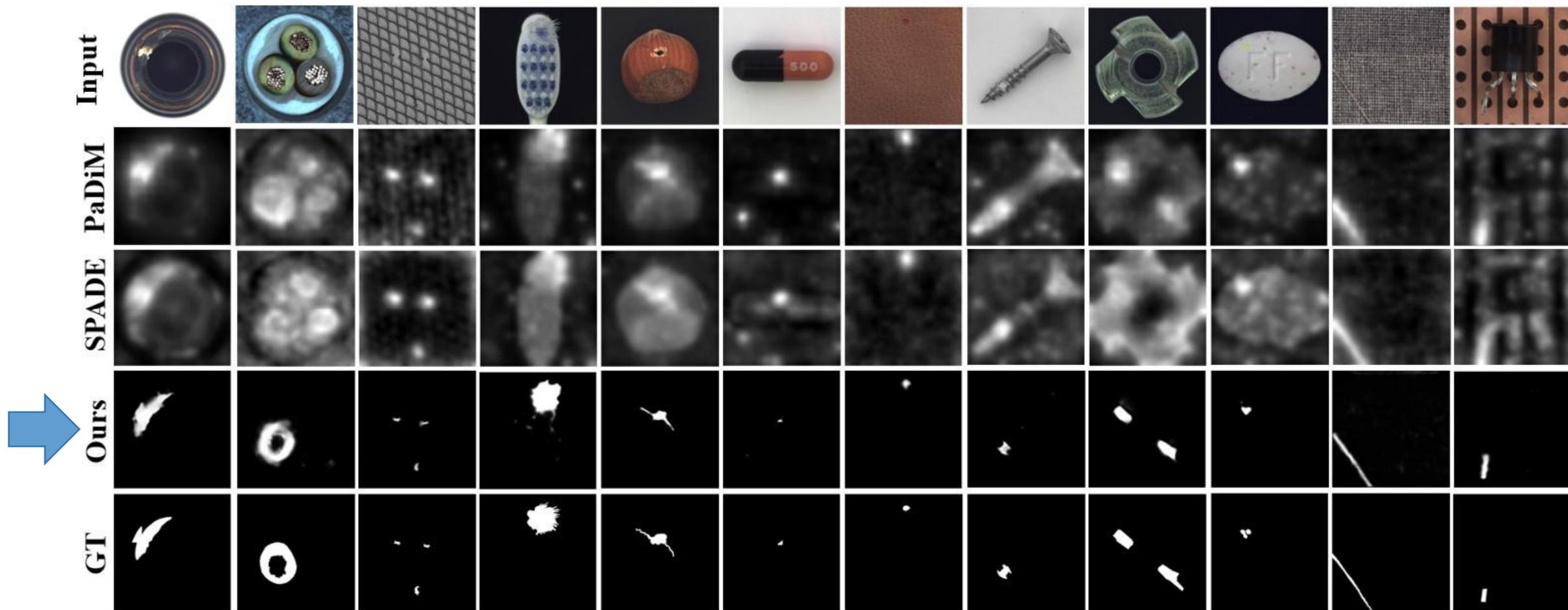


# MemSeg: 一种利用差异与共性的半监督图像表面缺陷检测方法



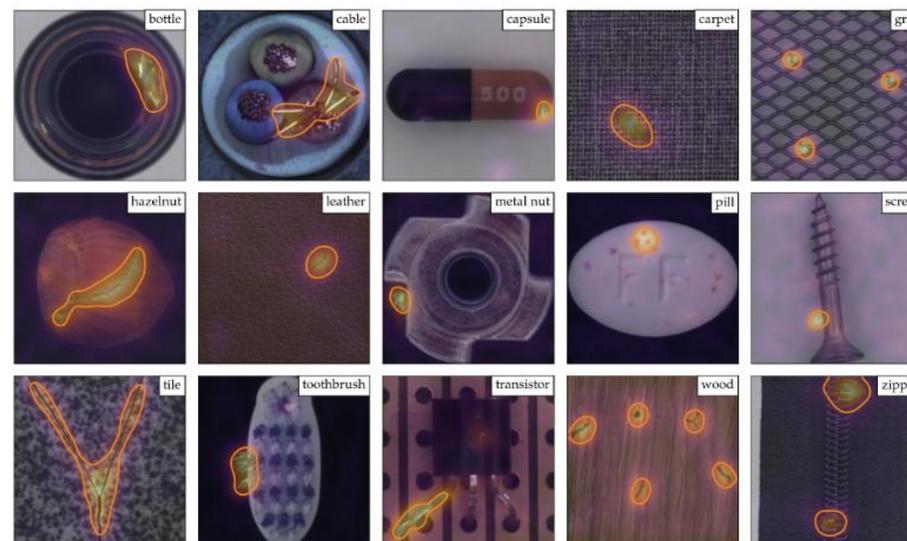
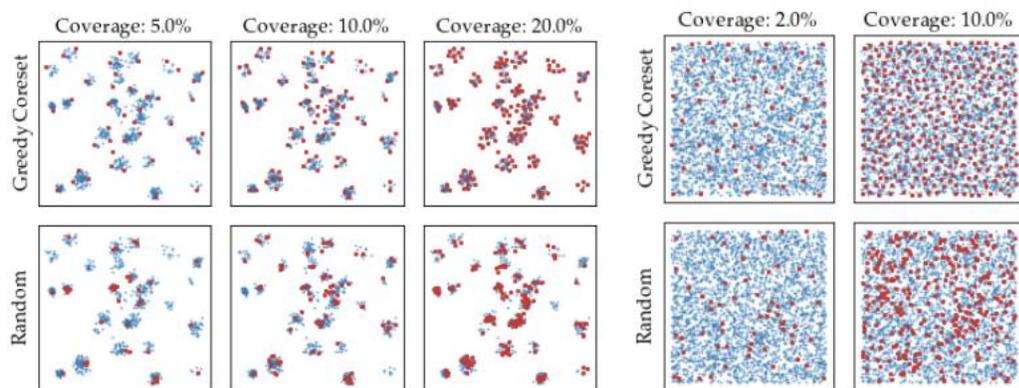
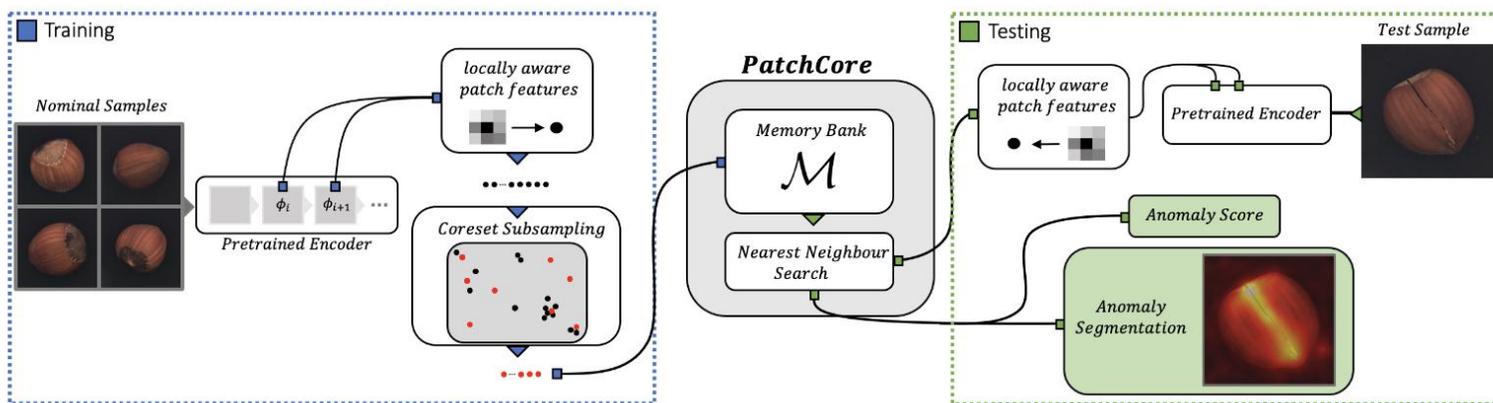
M. Yang, P. Wu, J. Liu, H. Feng, Memseg: A semi-supervised method for image surface defect detection using differences and commonalities. arXiv preprint arXiv:2205.00908 (2022)

# MemSeg: 一种利用差异与共性的半监督图像表面缺陷检测方法

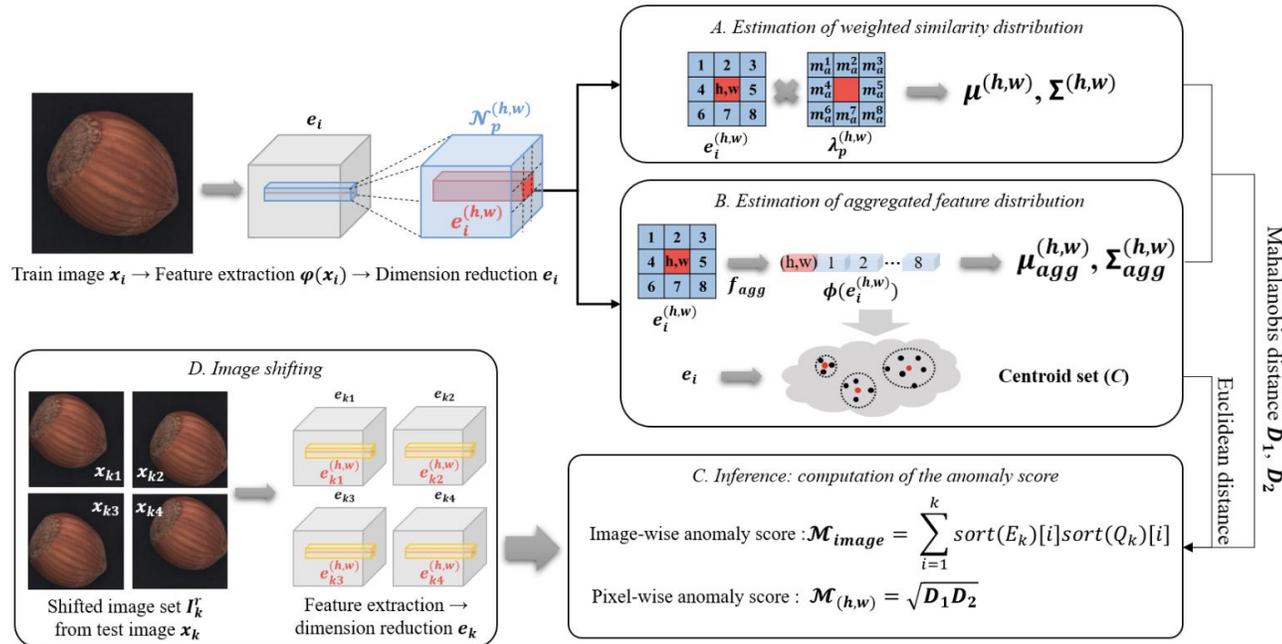


# PatchCore: 迈向工业异常检测中的全面召回

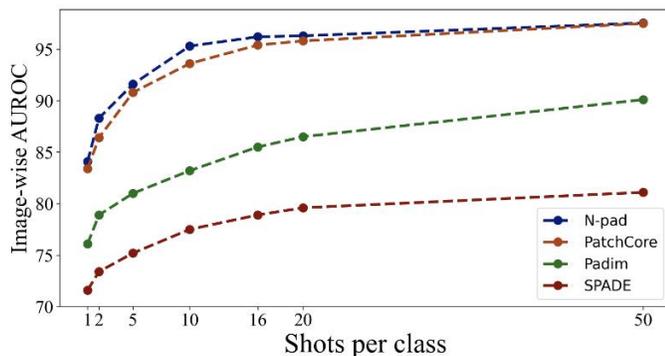
K. Roth, L. Pemula, J. Zepeda, B. Schölkopf, T. Brox, P. Gehler,  
Towards total recall in industrial  
anomaly detection. Proceedings of  
the IEEE/CVF Conference on  
Computer Vision and Pattern  
Recognition pp. 14,318–14,328  
(2022)



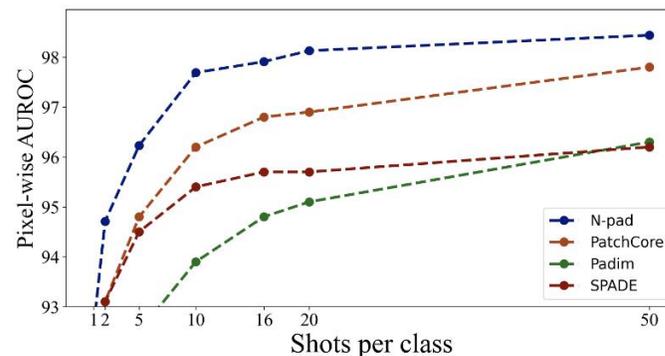
# N-pad: 基于相邻像素的工业异常检测



J. Jang, E. Hwang, S.H. Park, N-pad: Neighboring pixel-based industrial anomaly detection. arXiv preprint arXiv:2210.08768 (2022)



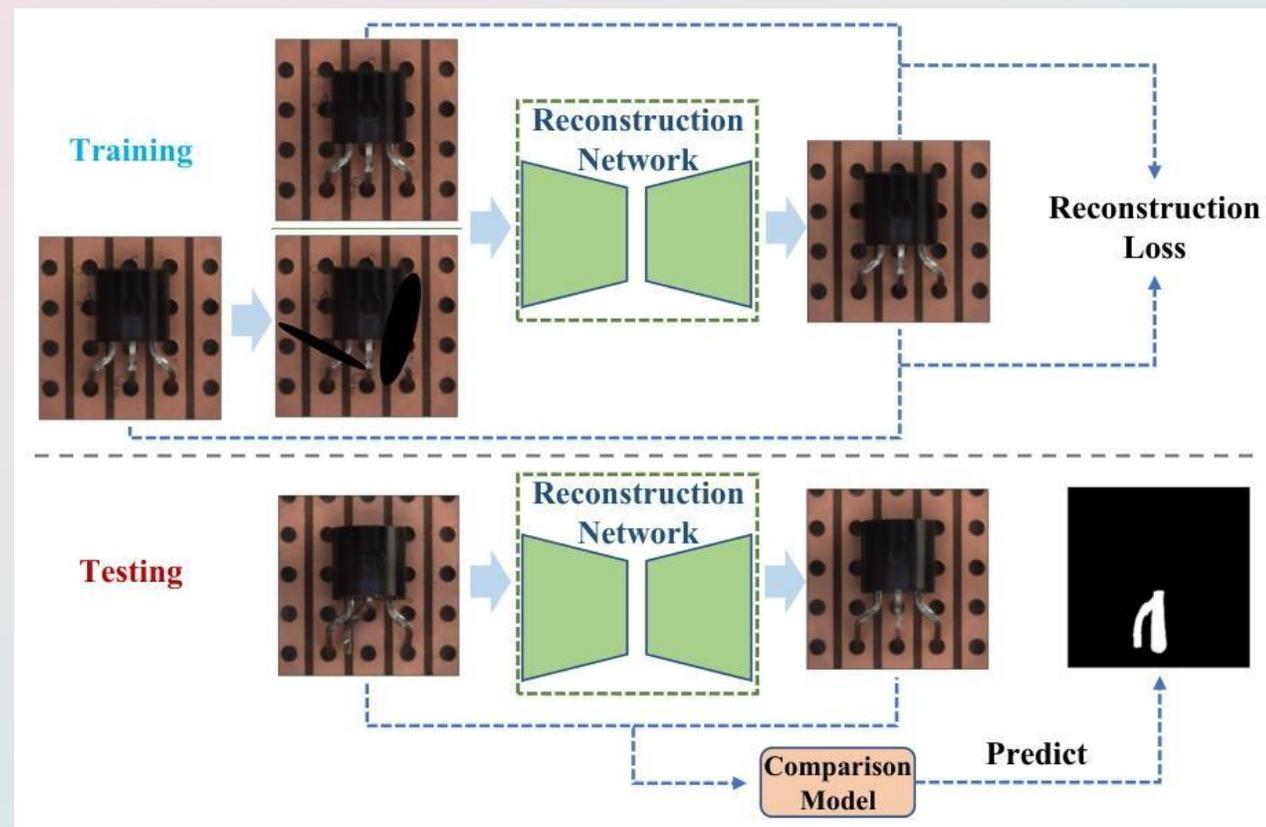
(a) Image-wise AUROC comparison of different models.



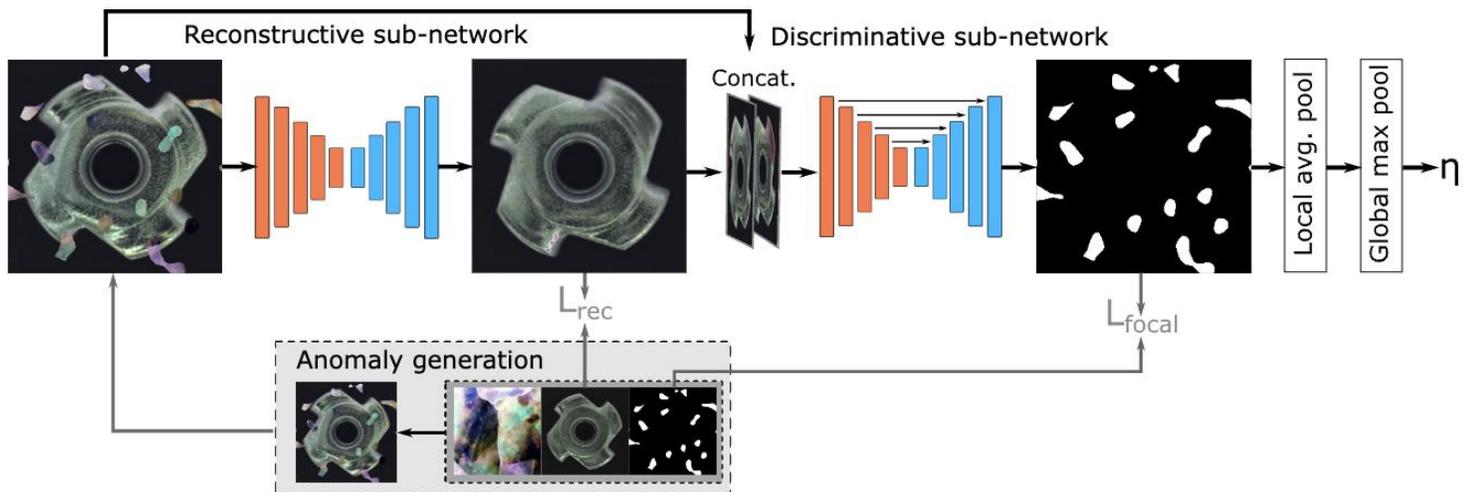
(b) Pixel-wise AUROC comparison of different models.

# 重构方法

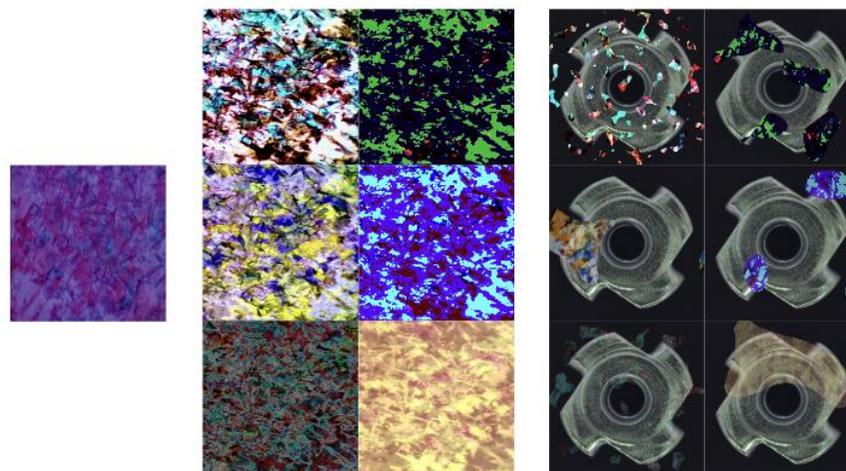
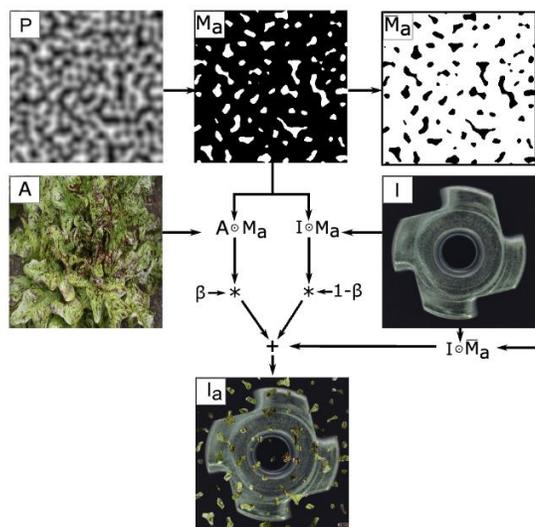
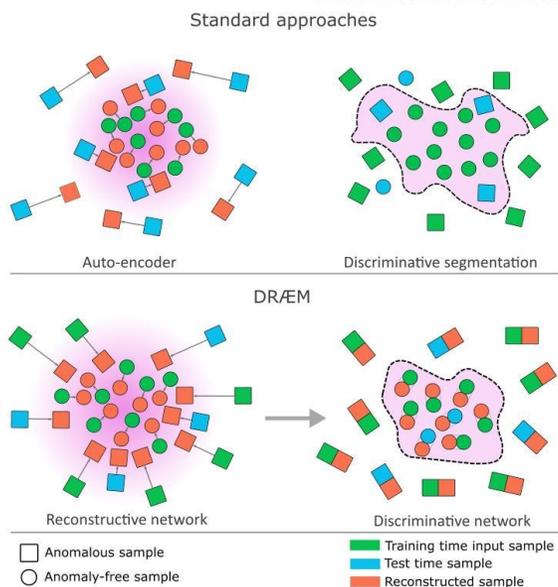
- 通过自编码器、GAN 等重构图像，利用重构误差检测异常
- 或者学习缺陷分布产生高保真缺陷样本
- 优势：像素级性能优于特征嵌入方法。



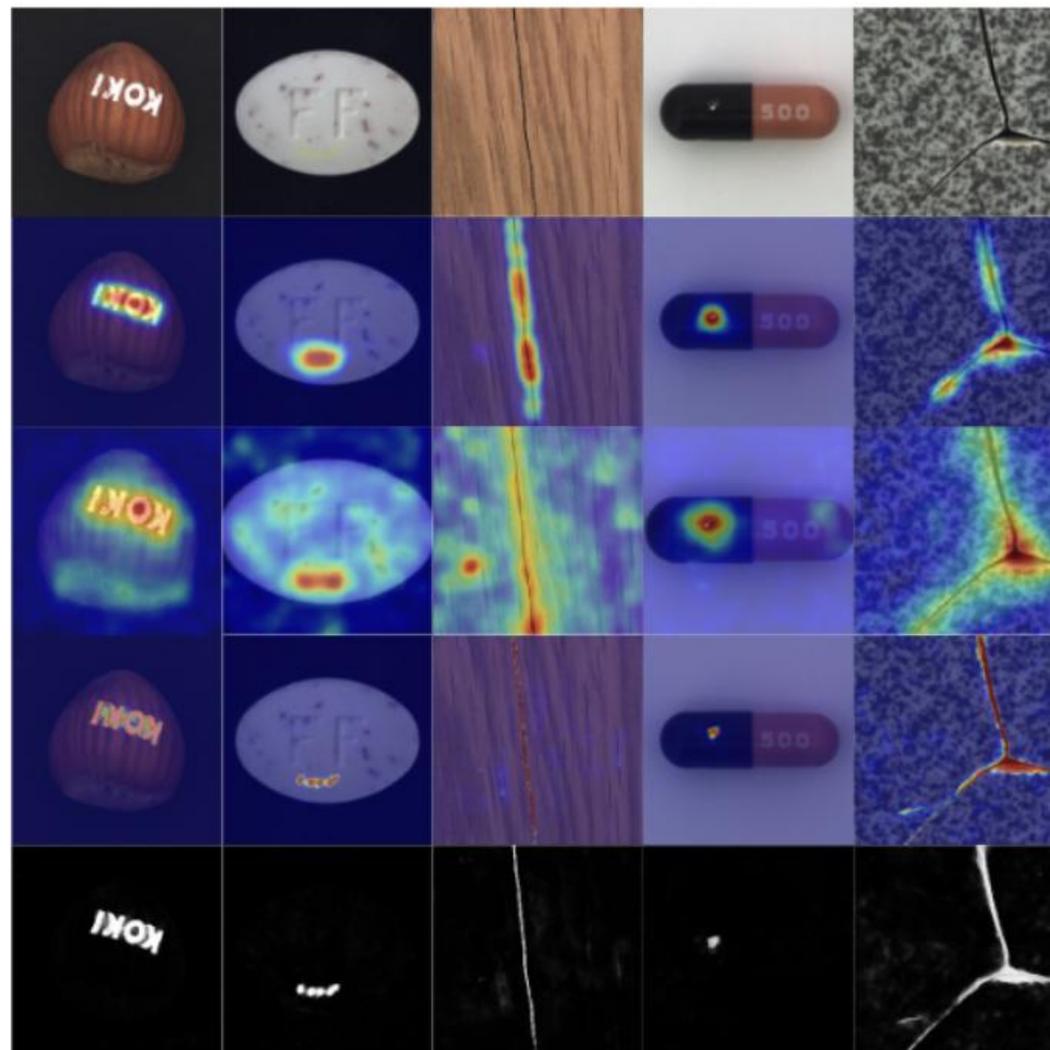
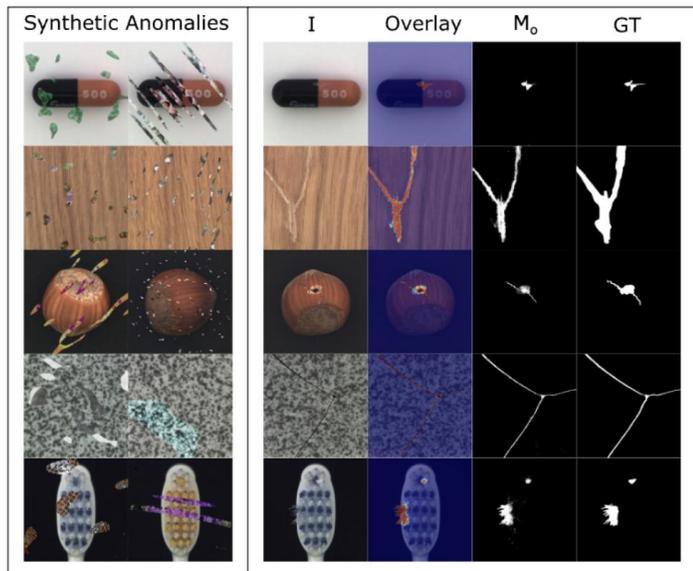
# DRAEM: 一种用于表面异常检测的判别训练重建嵌入方法



V. Zavrtanik, M. Kristan, D. Sko<sup>ˇ</sup>c aj, Draem—a discriminatively trained reconstruction embedding for surface anomaly detection. Proceedings of the IEEE/CVF International Conference on Computer Vision pp. 8330– 8339 (2021)



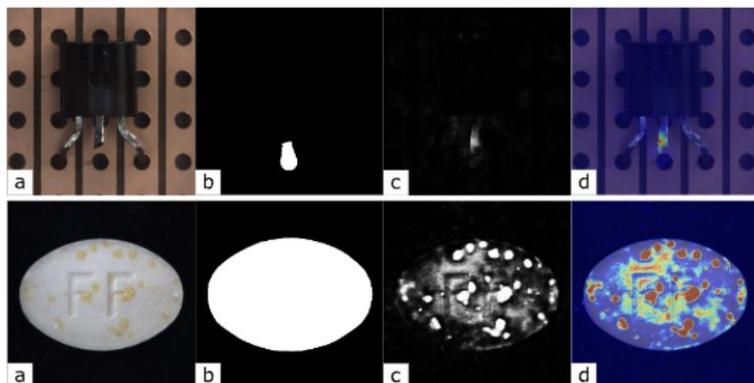
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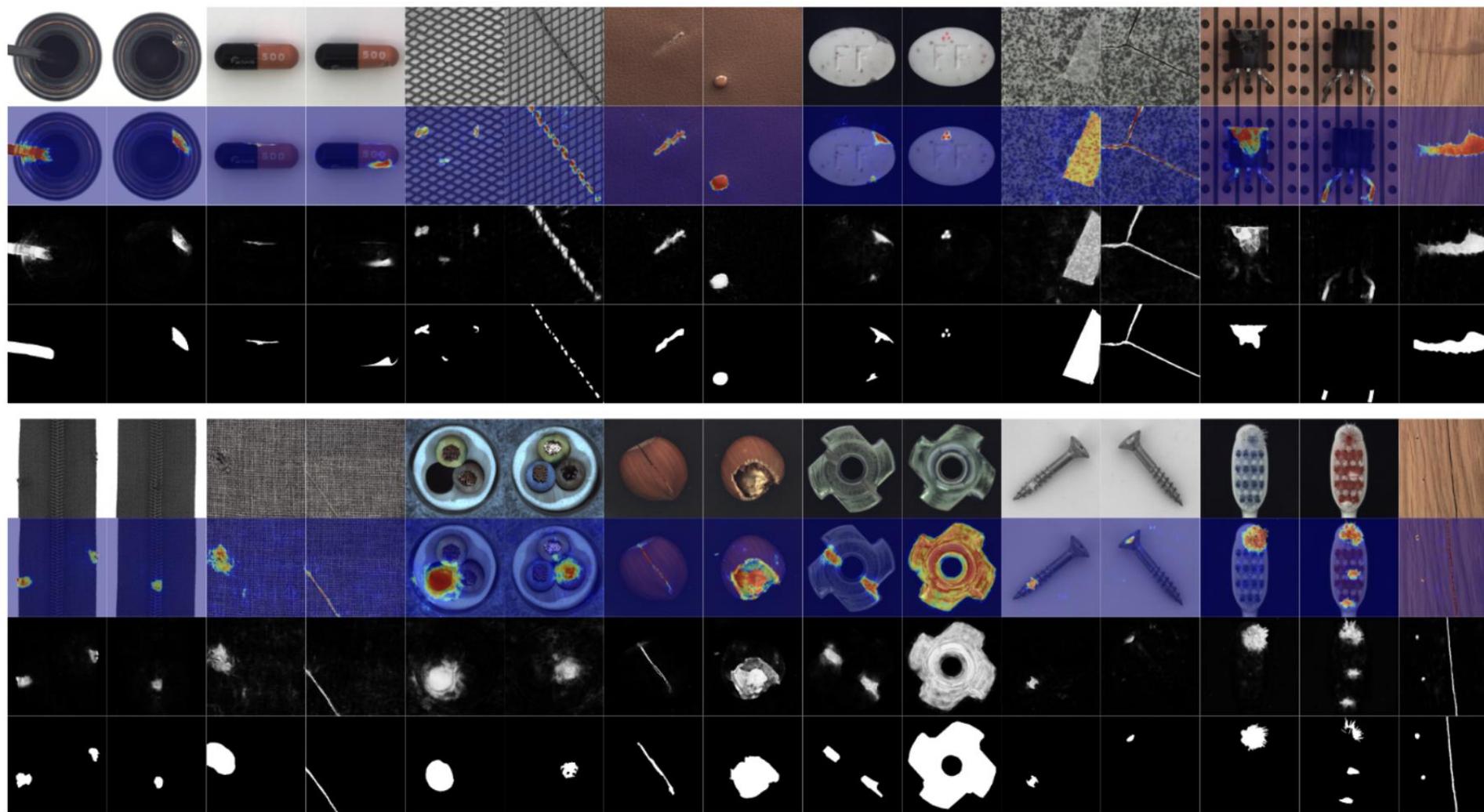
Uniform Student

PaDim

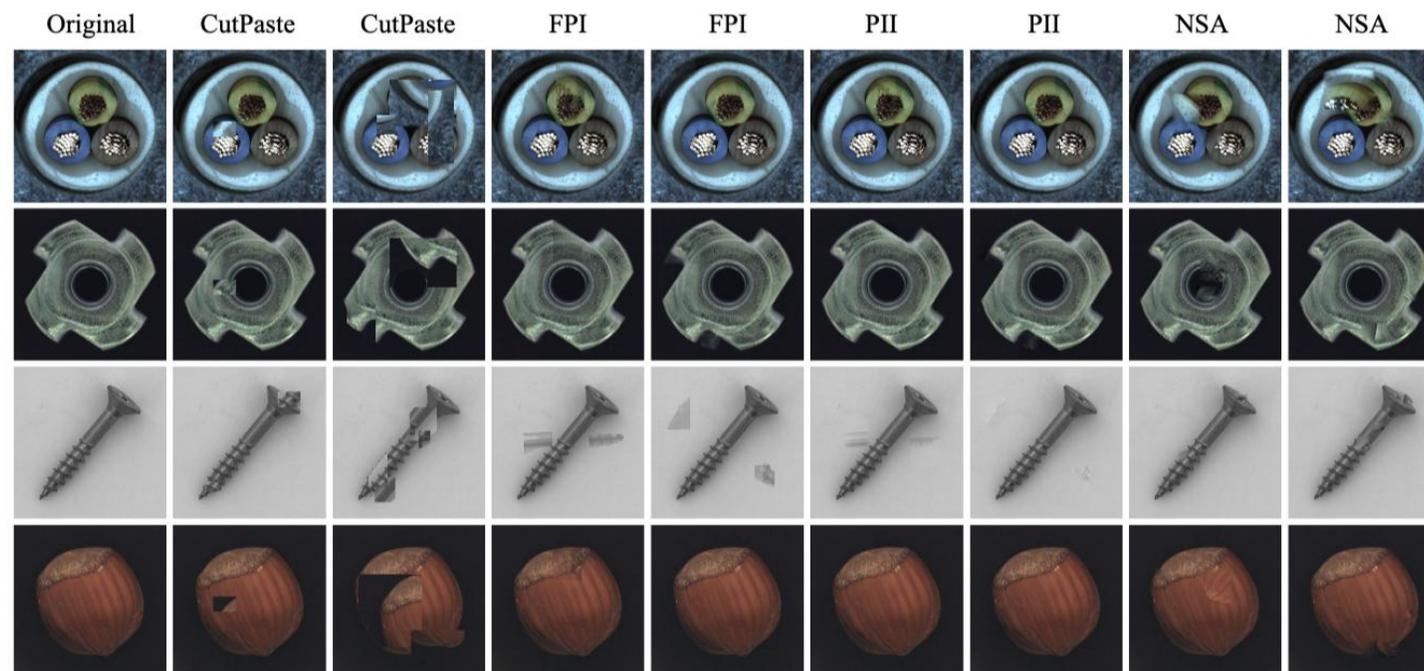
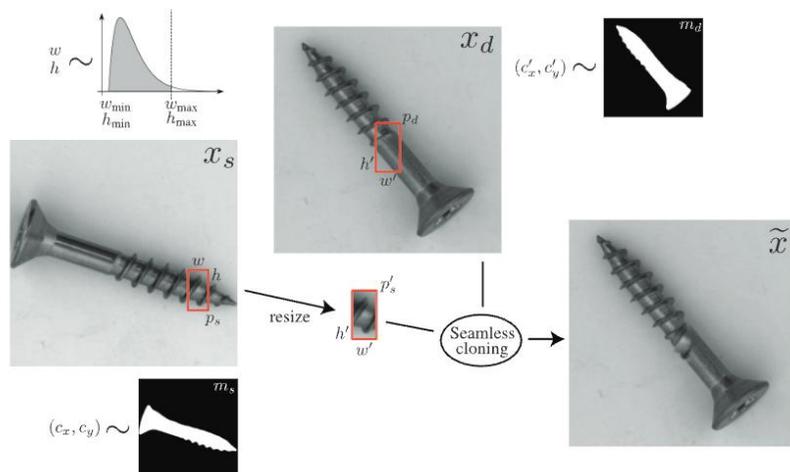
DRAEM



# DRAEM: 一种用于表面异常检测的判别训练重建嵌入方法

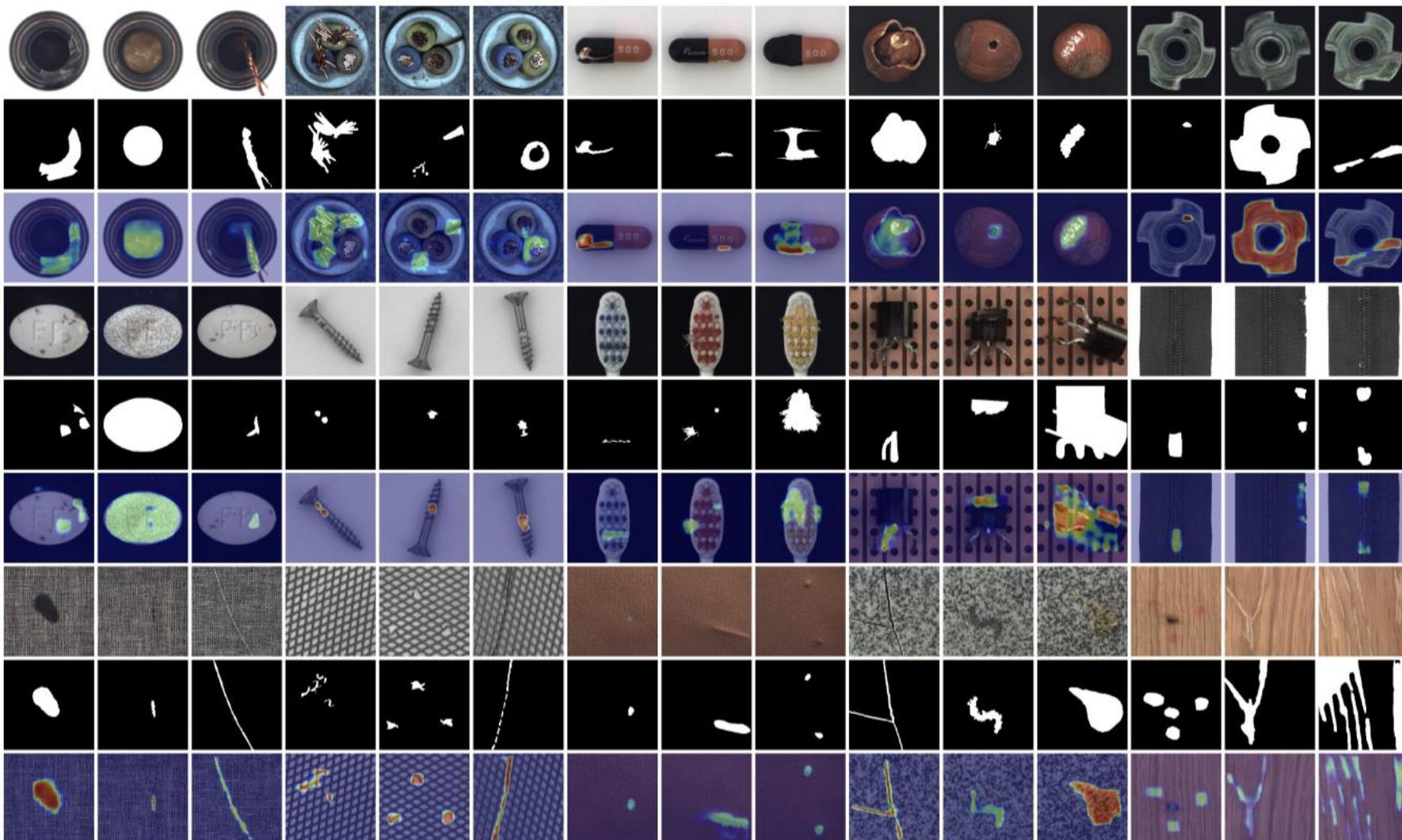


# NSA: 用于自监督异常检测与定位的自然合成异常

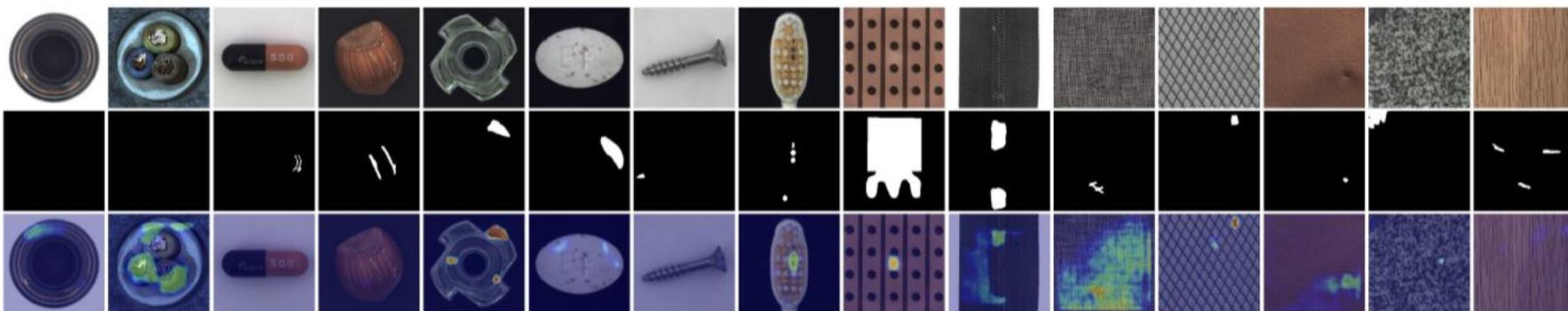
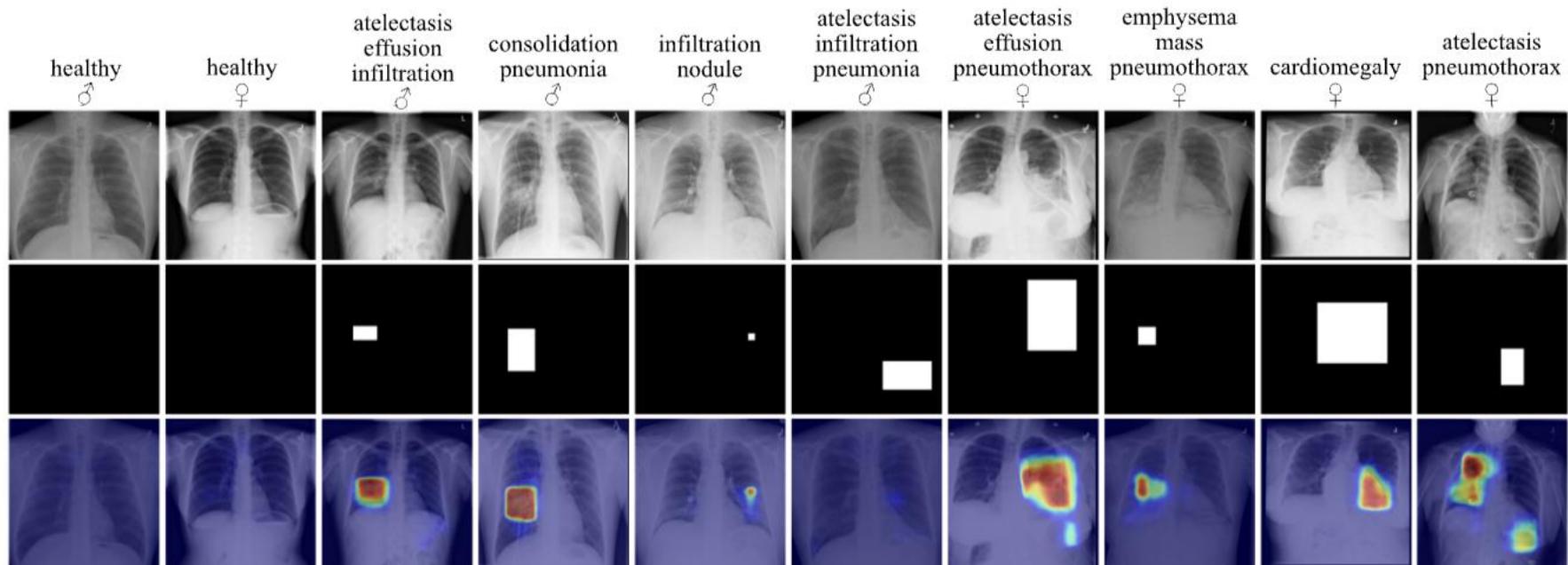


H.M. Schlüter, J. Tan, B. Hou, B. Kainz, Natural synthetic anomalies for self-supervised anomaly detection and localization. European Conference on Computer Vision pp. 474–489 (2022)

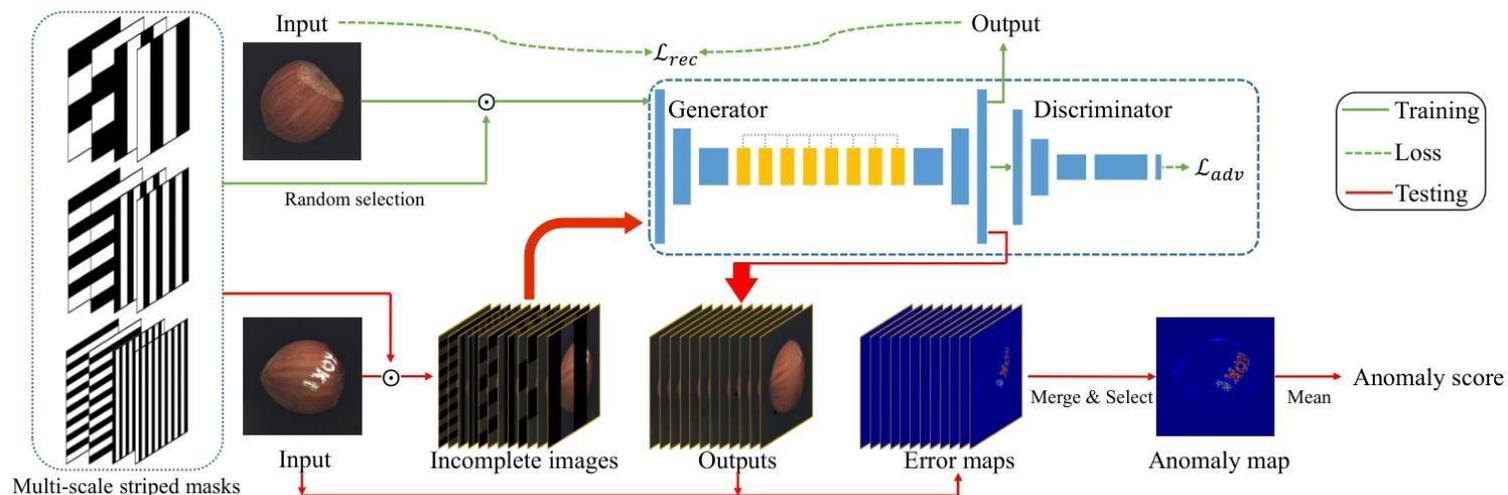
# NSA: 用于自监督异常检测与定位的自然合成异常



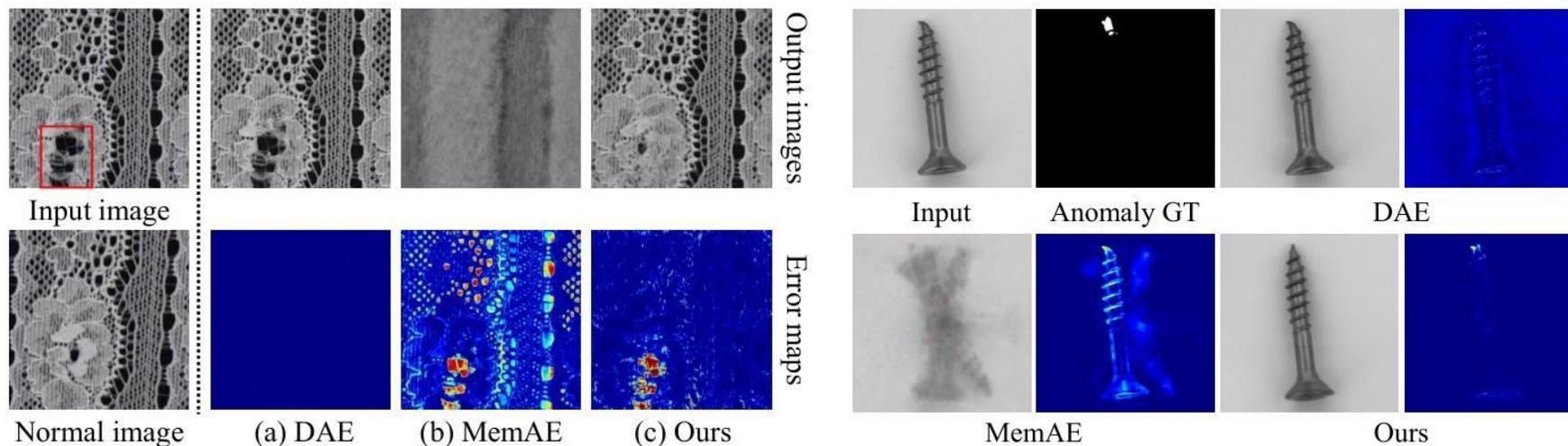
# NSA: 用于自监督异常检测与定位的自然合成异常



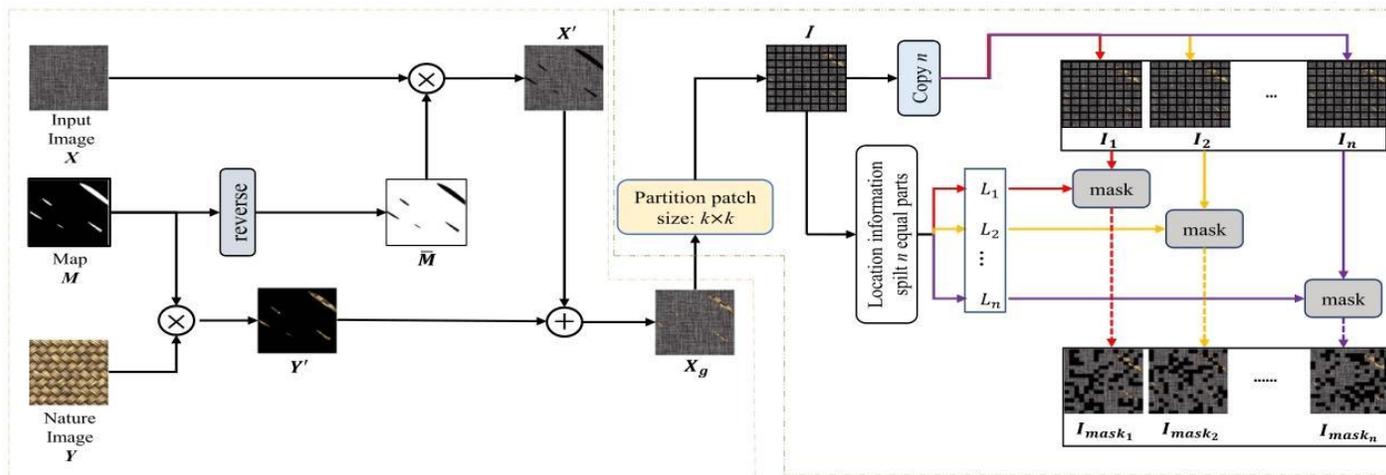
# SCADN: 从正常样本中学习语义上下文用于无监督异常检测



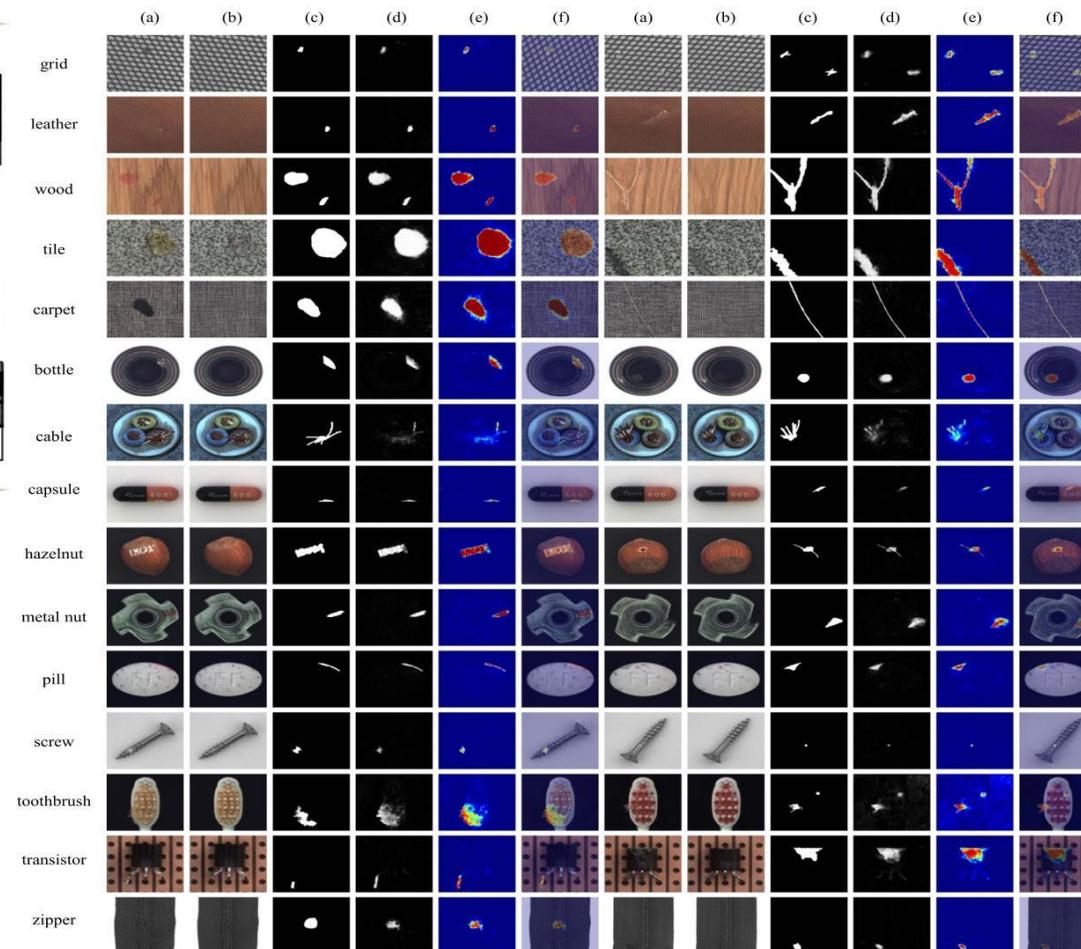
X. Yan, H. Zhang, X. Xu, X. Hu, P.A. Heng, Learning semantic context from normal samples for unsupervised anomaly detection. Proceedings of the AAAI Conference on Artificial Intelligence 35(4), 3110–3118 (2021)



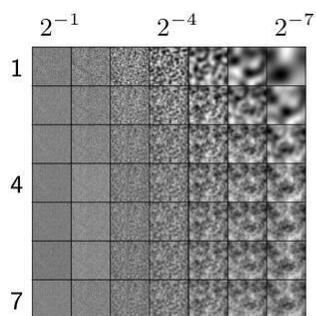
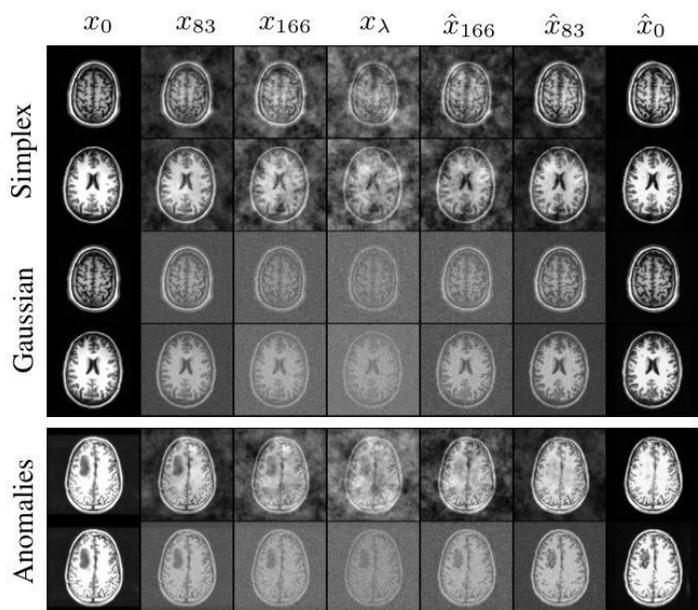
# 用于工业异常检测的掩码Swin Transformer UNet



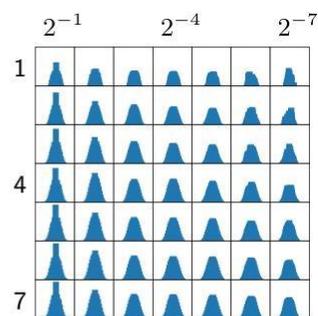
J. Jiang, J. Zhu, M. Bilal, Y. Cui, N. Kumar, R. Dou, F. Su, X. Xu, Masked swin transformer unet for industrial anomaly detection. IEEE Transactions on Industrial Informatics (2022)



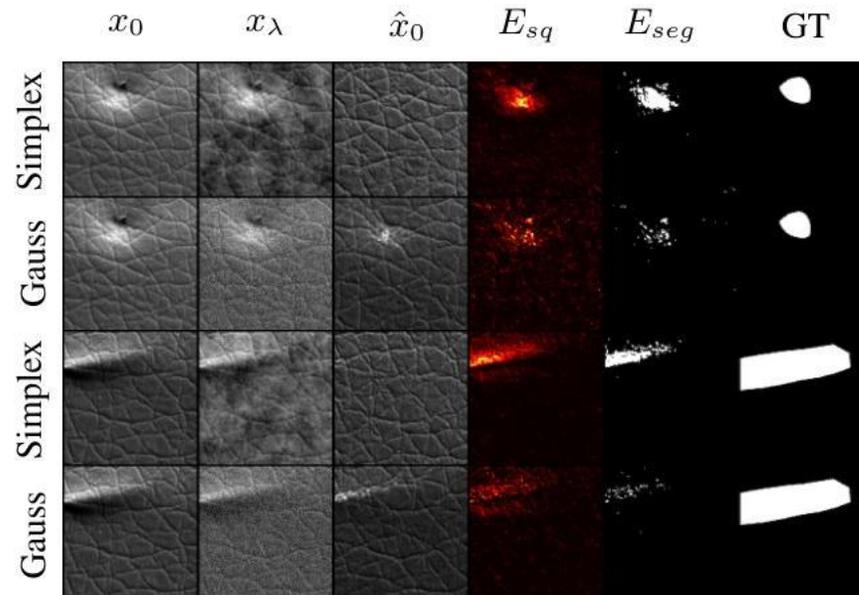
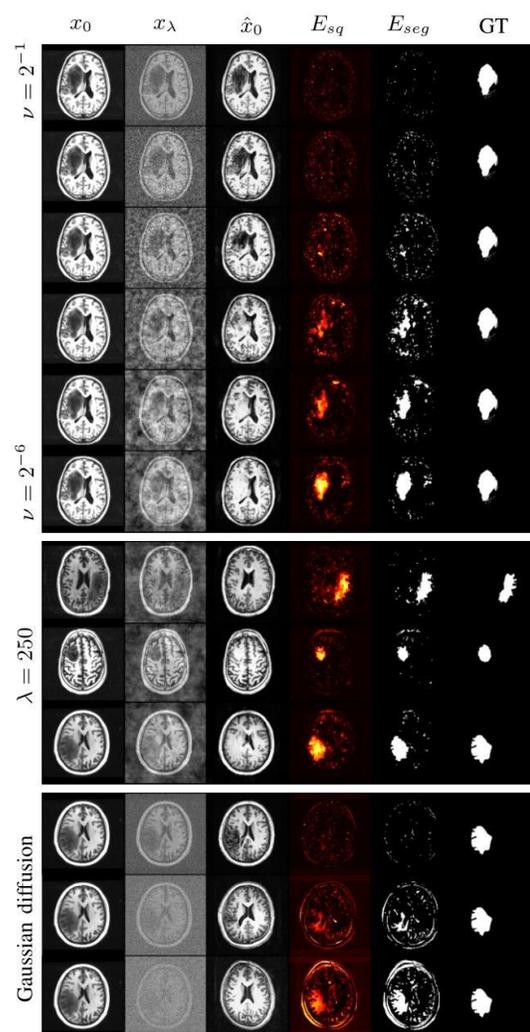
# AnoDDPM: 使用单纯形噪声的去噪扩散概率模型异常检测



(a) Structures of simplex noise



(b) Histograms of simplex noise



J. Wyatt, A. Leach, S.M. Schmon, C.G. Willcocks, Anoddpm: Anomaly detection with denoising diffusion probabilistic models using simplex noise. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition pp. 650–656 (2022)

# 光纤端面/光芯片缺陷检测

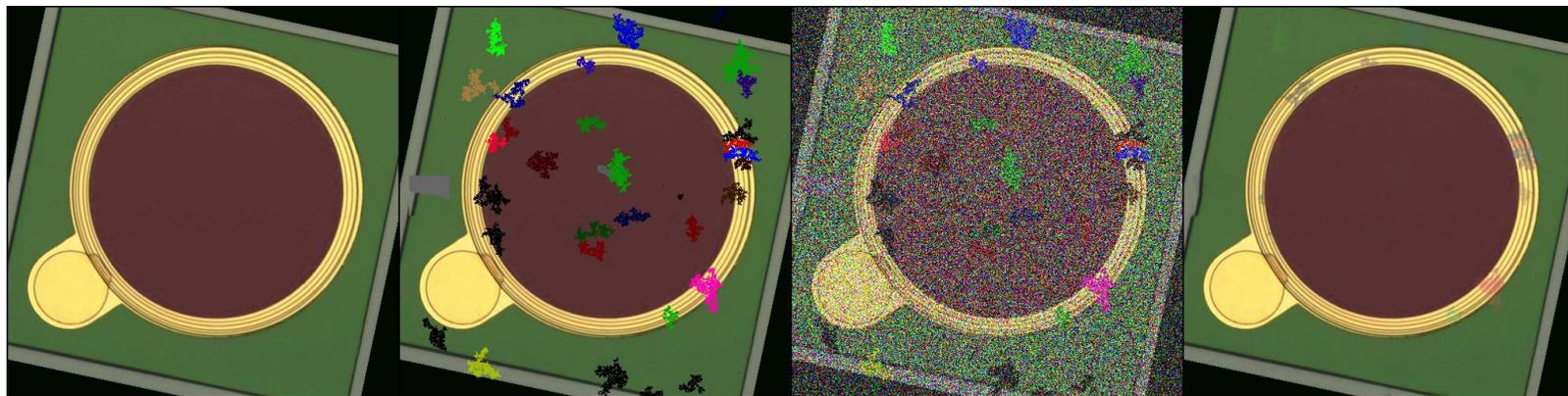
ChipDiffusion



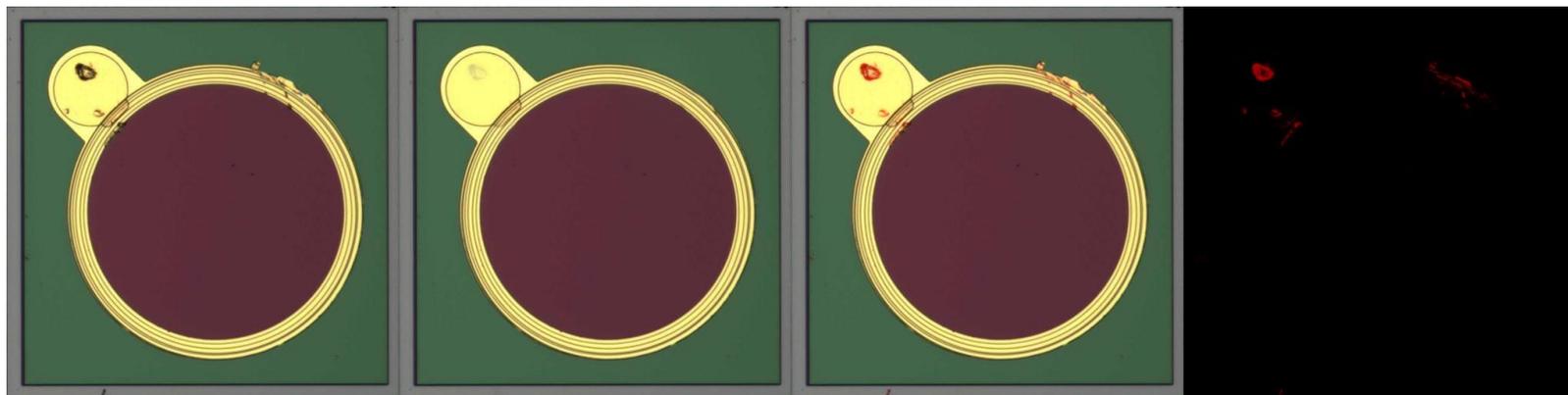
# ChipDiffusion

- ChipDiffusion是无监督高精度芯片缺陷检测工具
- 利用扩散模型重建被添加伪缺陷图像，隐式学习正样本模式，同时能面向缺陷泛化

原始图，伪缺陷图，加噪图，重建图

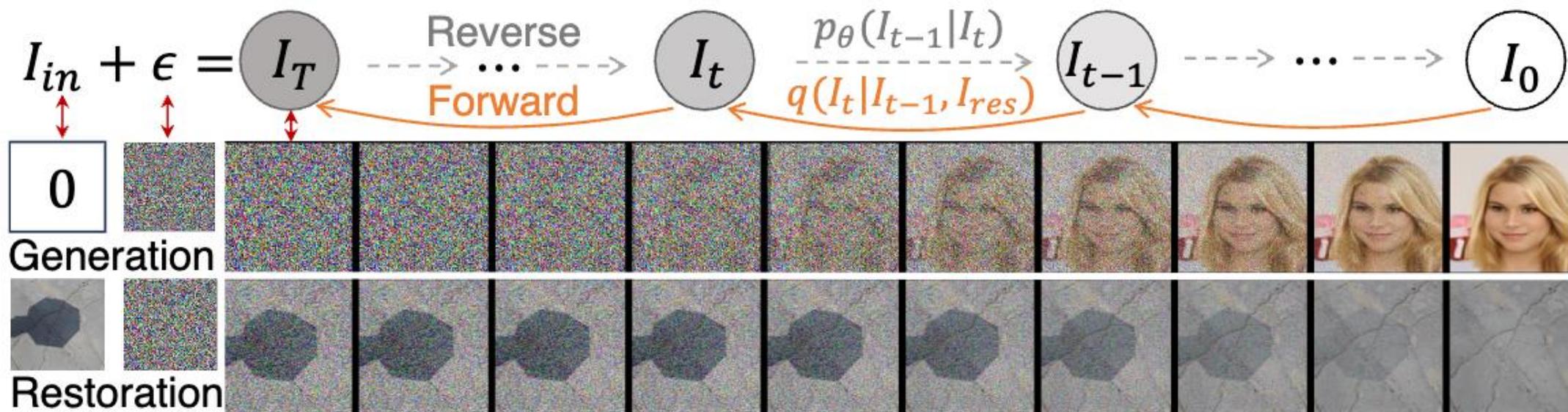


真实缺陷，重建图，缺陷遮罩图



# ChipDiffusion模型

- 向图像中添加噪声后去噪，在去噪的同时去除缺陷



- 去除的噪声部分由Unet模型预测

# 数据增强 (Data Augmentation)

1. 检测目标：学习缺陷的本质特征

模型需要精准识别缺陷的 形态(Shape)与纹理(Texture)。

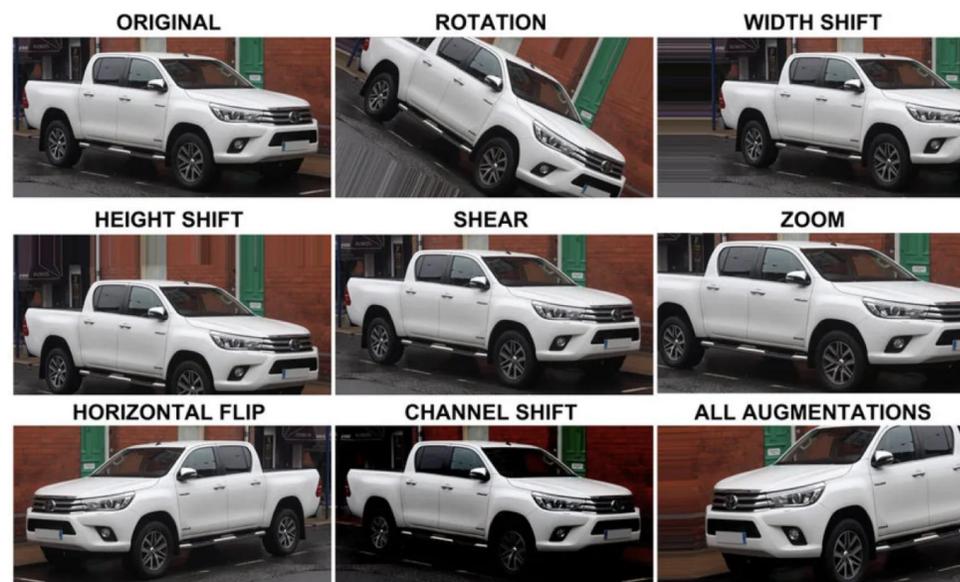
2. 挑战：剥离无关因素的干扰

在真实工业环境中，图像会受到各种因素影响。包括光照的明暗变化，颜色的细微差异，旋转的不同角度，位置的随机出现等

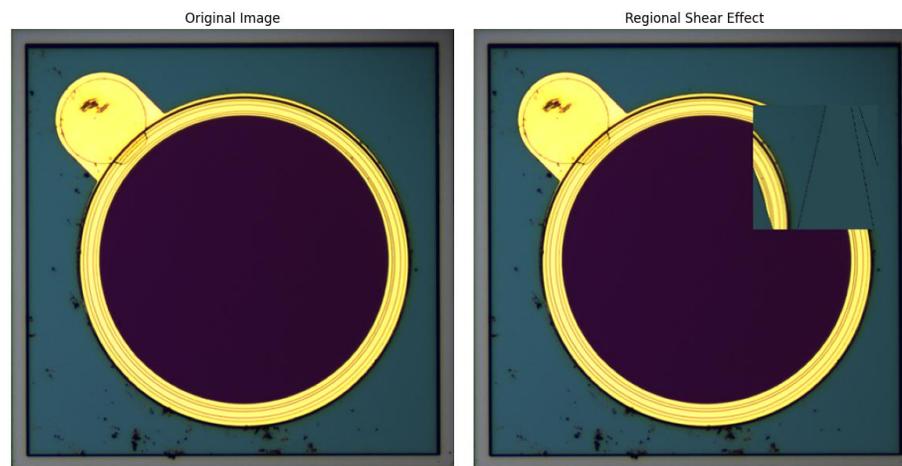
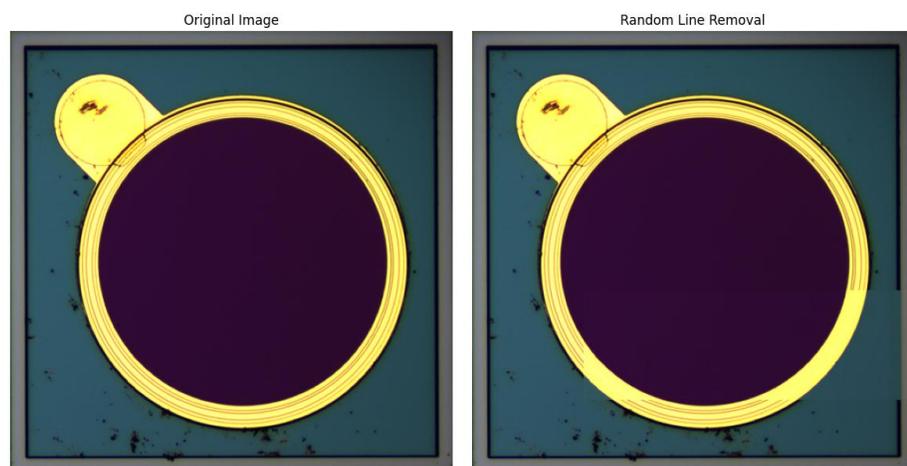
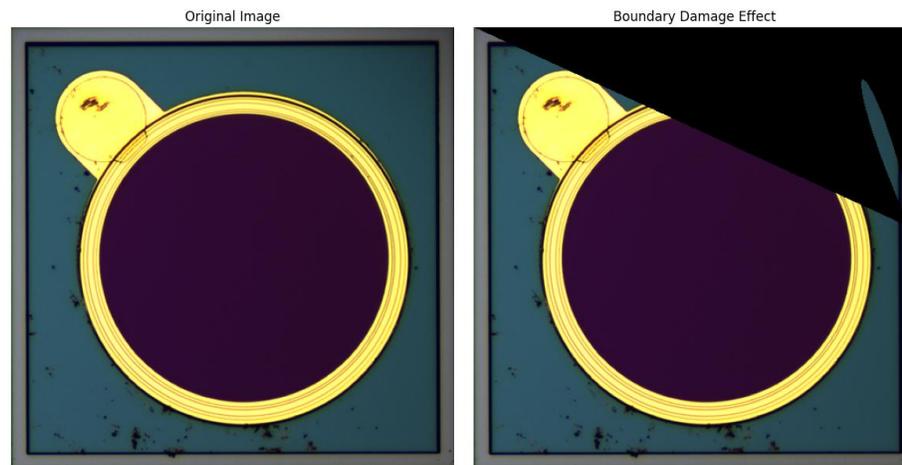
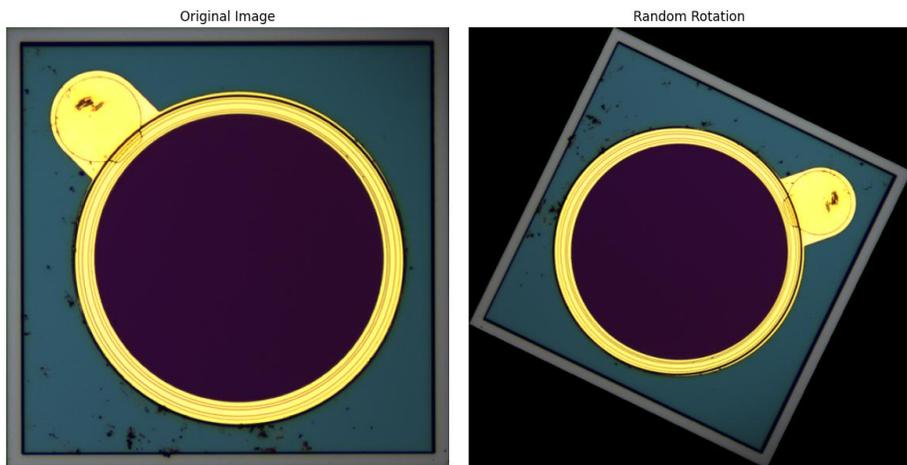
3.数据增强 (Data Augmentation)

创造海量数据： 用有限的样本生成大量看似不同但本质相同的训练数据。

提升泛化能力： 让模型在各种干扰下都能认出缺陷，变得更“聪明”、更“鲁棒”。



# 光芯片数据增强 (形态)



# 光芯片数据增强 (颜色)

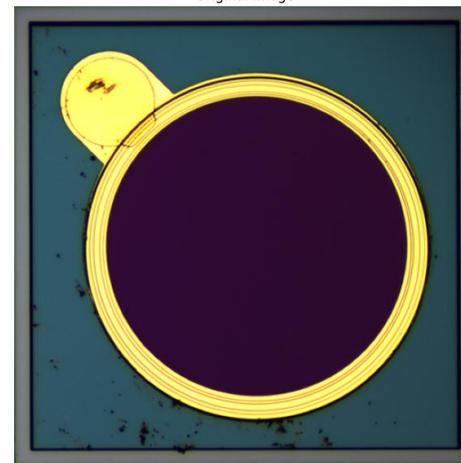
Original Image



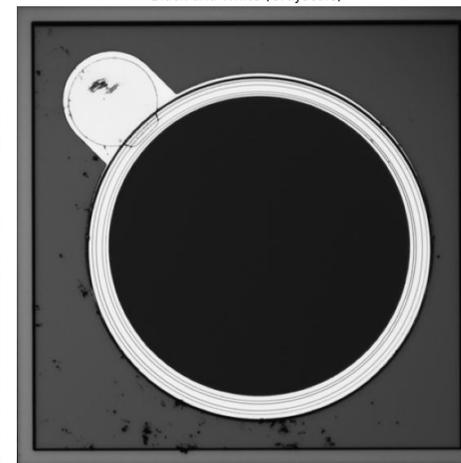
Color Temperature (Warm)



Original Image



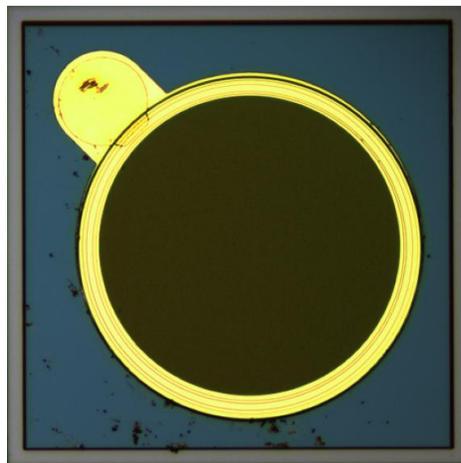
Black and White (Grayscale)



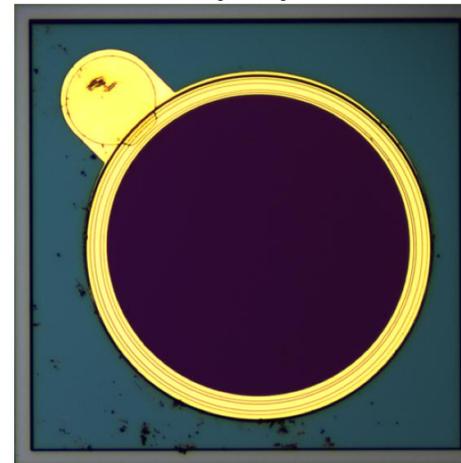
Original Image



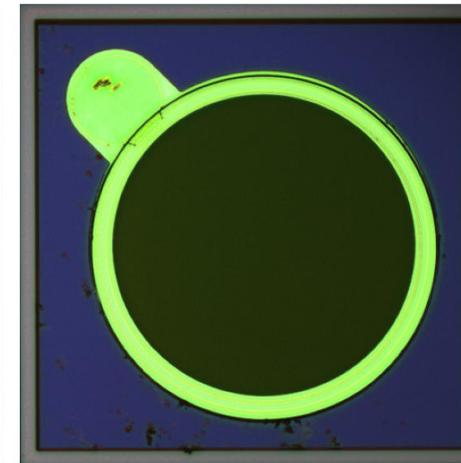
Random Color Shift



Original Image



Hue Shift



# 像素级性能

ChipDiffusion表现出了  
优异的像素级缺陷检测  
能力

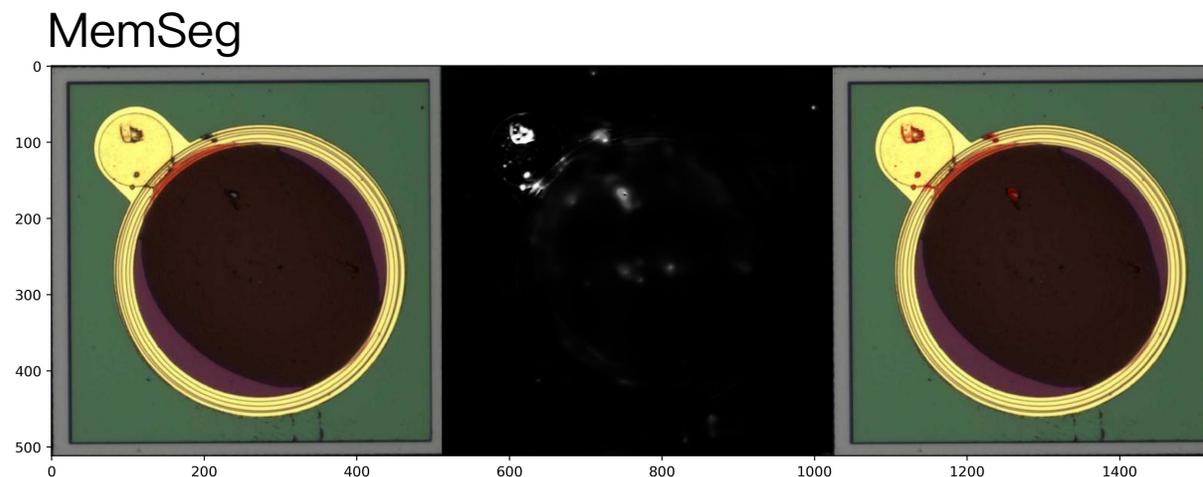
模型性能：

eval\_AUROC-pixel :

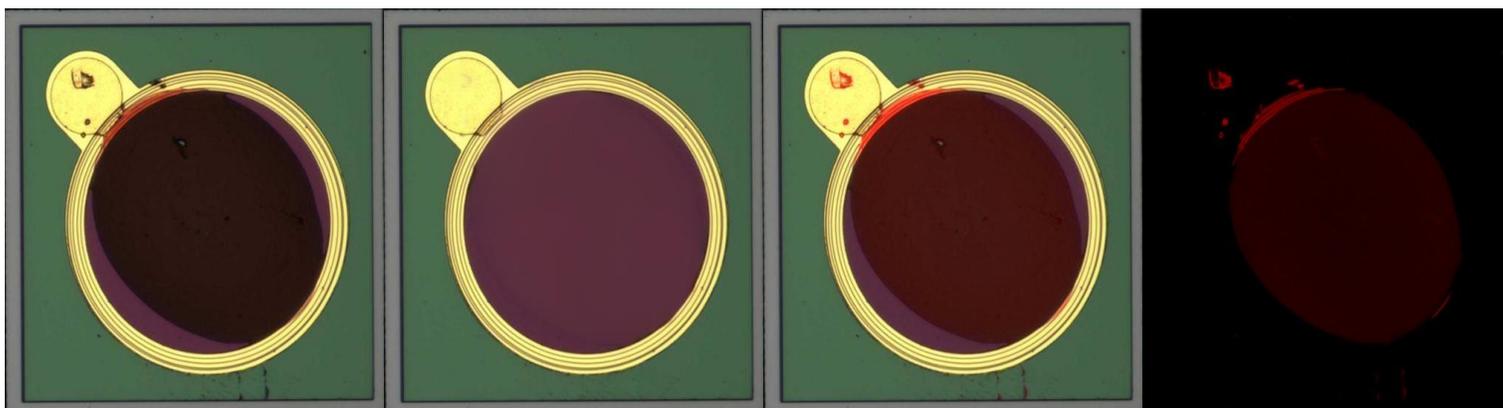
99.5%\*

eval\_IoU-mask:

99.3%\*

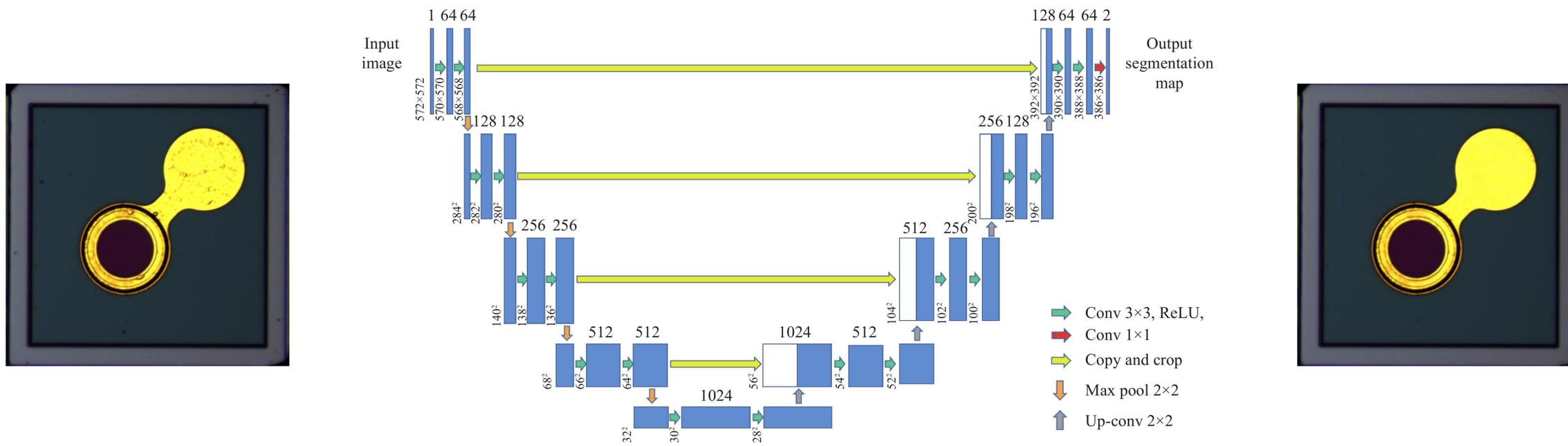


ChipDiffusion

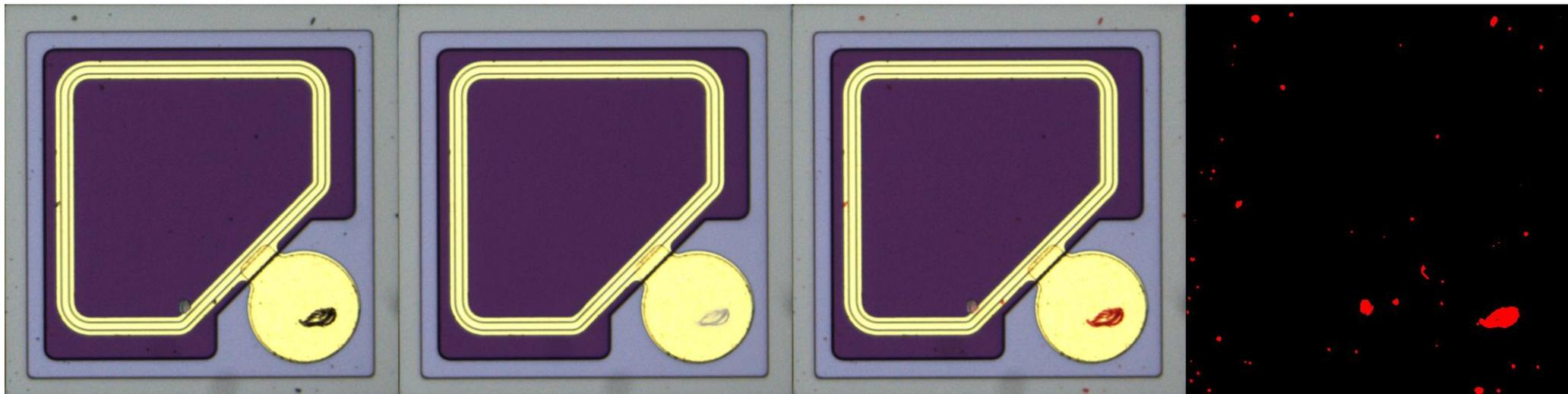


# 模型蒸馏

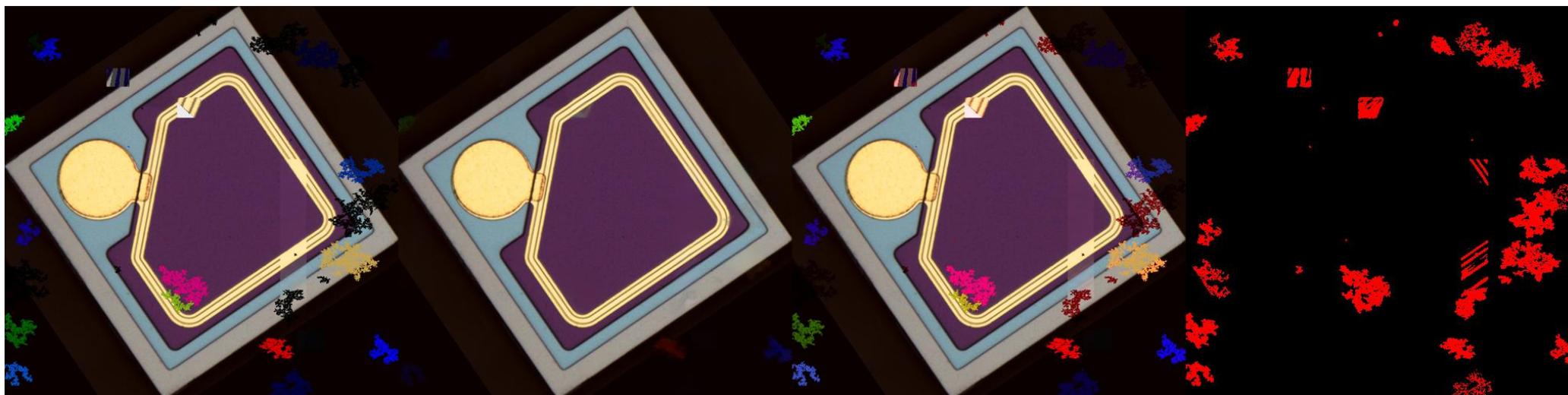
- 光芯片检测使用Diffusion模型需要多轮降噪，顺序推理速度慢。因此采用ChipDiffusion产生带标注的缺陷数据集，有监督训练小模型实现高精度快速检测，满足产线要求。
- 我们训练了一个Unet小模型，输入缺陷图像直接重建出无缺陷图像，推理时间从3s提升到0.2s



# 模型性能（光芯片泛化）

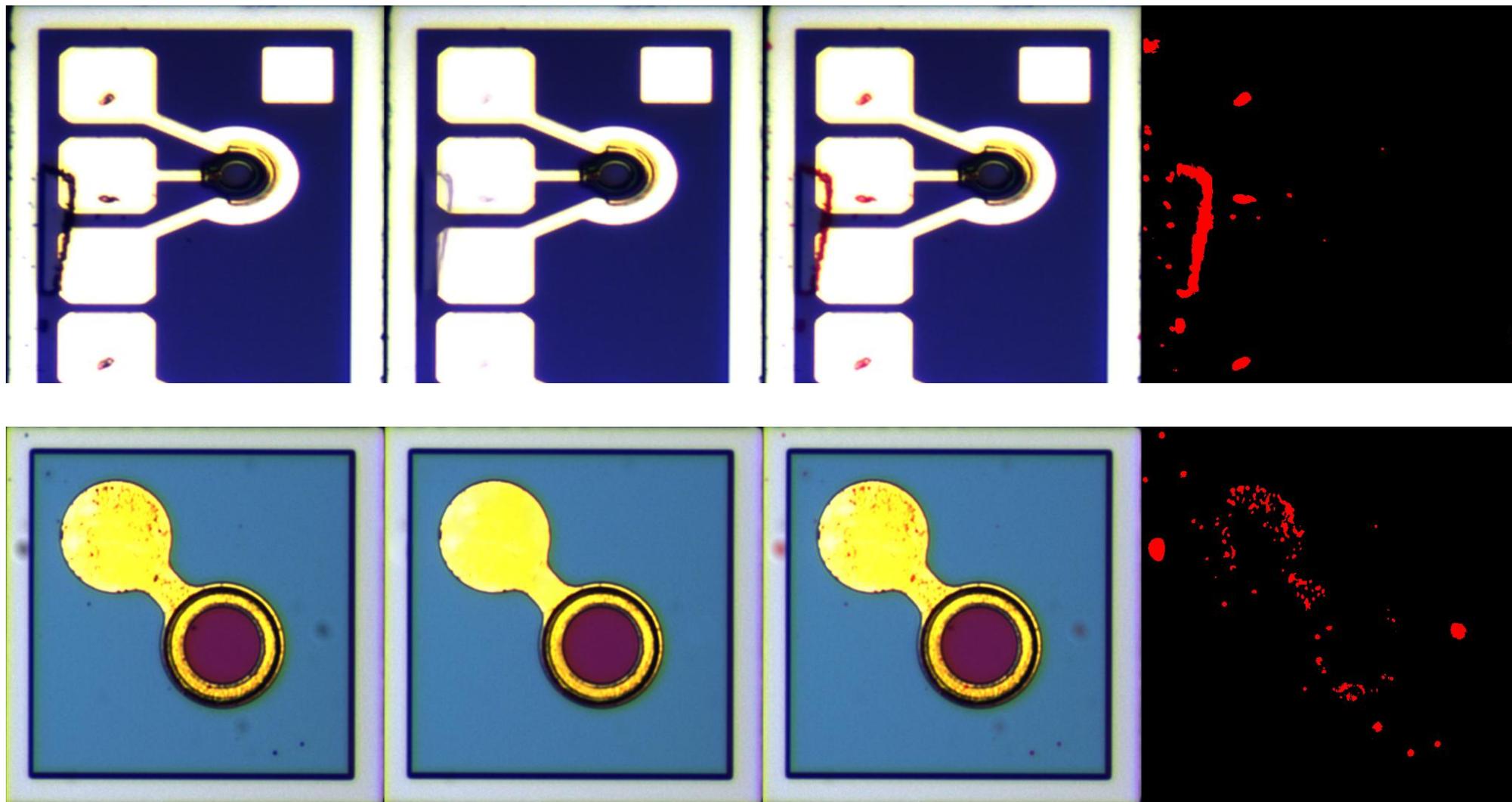


真实数据（无训练）



训练增强数据

# 模型性能（不同芯片泛化）



# 模型性能（色彩泛化）



# 光纤端面模型

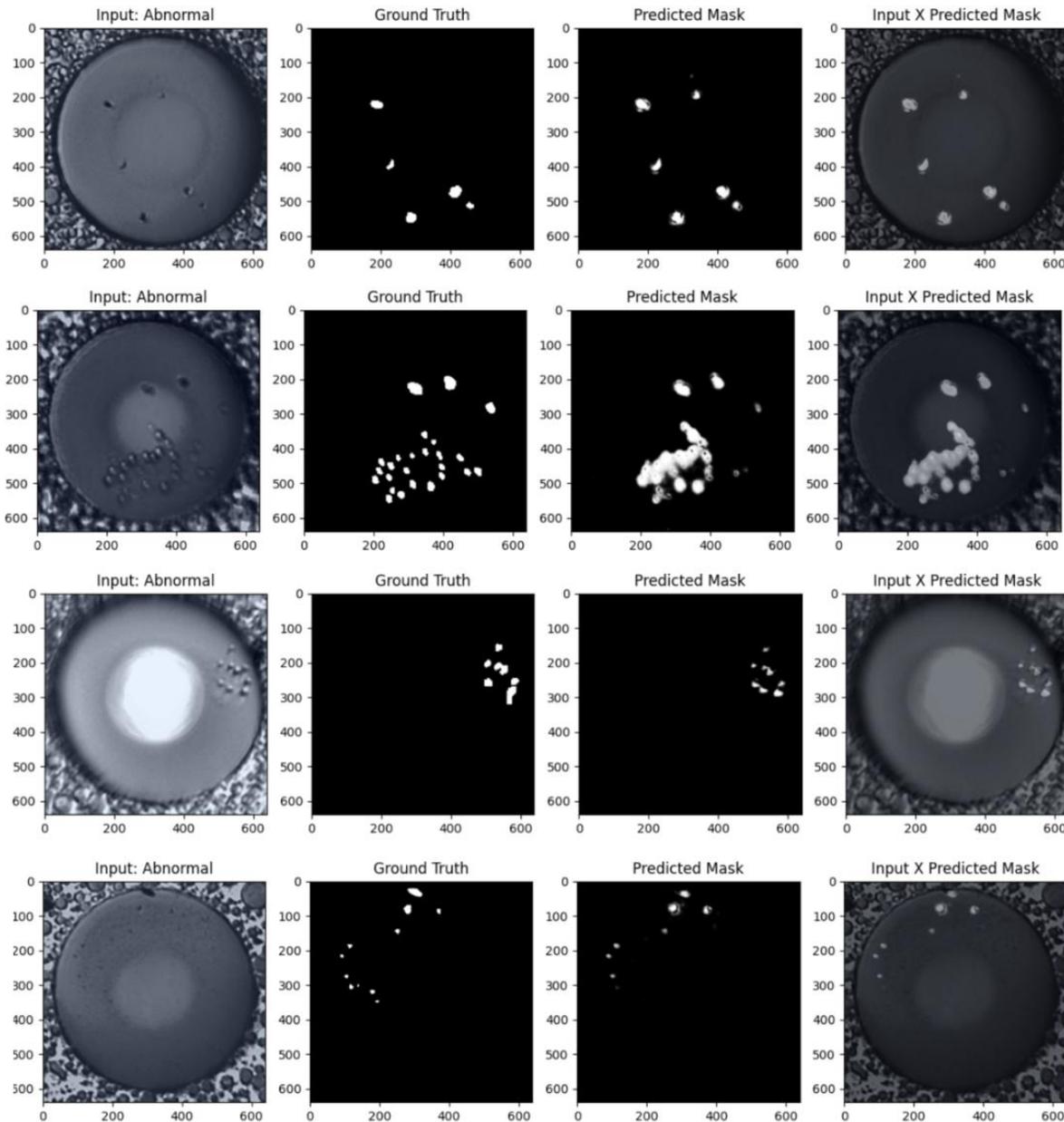
模型性能:

eval\_AUROC-image :

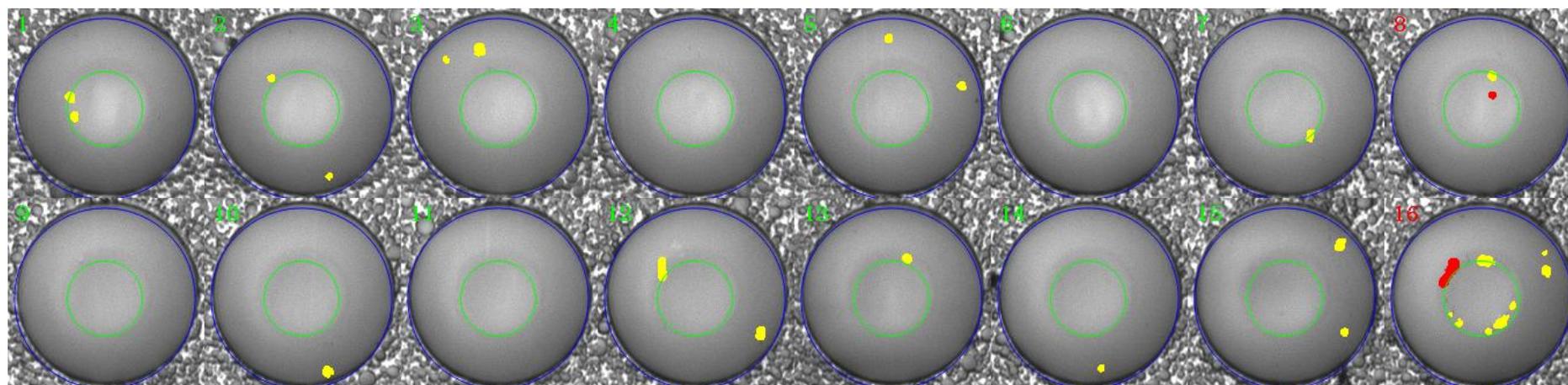
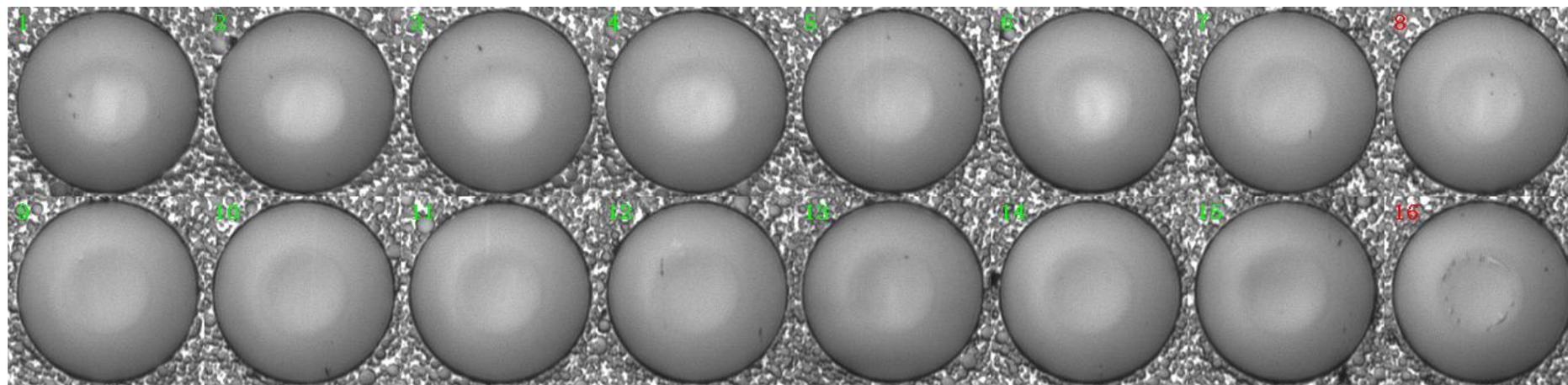
0.993

eval\_AUROC-pixel :

0.983



# 光纤端面检测效果



# 总结

- 人工智能对于自动化芯片缺陷检测具有重要意义；
- 工业生产实际需求需要系统化的解决方案；
- 未来有望实现通用缺陷检测模型。